

**AN EVALUATION OF HOME HOSPITAL CARE IMPACTS ON
EMERGENCY DEPARTMENT BOARDING USING SIMULATION**

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John A. Fard

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AN EVALUATION OF HOME HOSPITAL CARE IMPACTS ON EMERGENCY DEPARTMENT BOARDING USING SIMULATION

Approved by:

Prof. Kathy Roper, Advisor
School of Building Construction
Georgia Institute of Technology

Dr. David Goldsman
School of Industrial and Systems
Engineering
Georgia Institute of Technology

Dr. Baabak Ashuri
School of Building Construction
Georgia Institute of Technology

Dr. Jeremy Hess
Department of Emergency Medicine,
Department of Environmental Health
Emory University

Dr. Pardis Pishdad-Bozorgi
School of Building Construction
Georgia Institute of Technology

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GLOSSARY

Acuity: a classification or level of the predicted resources required to care for a patient.

Ambulance Diversion: when hospitals request that ambulances avoid their ED and instead transport patients to other care facilities.

Diagnostic Related Group (DRG): a system for classifying inpatient stays into groups for the purposes of relating the types of patients a hospital treats to the costs incurred.

Emergency Department: a dedicated location of an acute care hospital facility serving unscheduled patients requesting emergency assessment.

Emergency Department (ED) Patient Boarding: a patient remains in the emergency department after the decision has been made to admit or transfer the individual due to a lack of available inpatient beds.

Home hospital: health care delivered by a health care professional providing active, short-term acute care in an individual's home for treatment that would otherwise necessitate inpatient admission in an acute care hospital.

Home care: see *home hospital*.

Remote care: see *home hospital*.

LIST OF SYMBOLS AND ABBREVIATIONS

ALOS	Average Length of Stay
CAP	Community Acquired Pneumonia
CHF	Chronic Heart Failure
COPD	Chronic Obstructive Pulmonary Disease
DES	Discrete Event Simulation
DRG	Diagnosis Related Group
ED	Emergency Department
EMS	Emergency Medical Services
FM	facility management
ICD	International Classification of Diseases
ICU	Intensive Care Unit
U.S.	United States

SUMMARY

The hospital emergency department (ED) is a critical source for health care amid a complex healthcare system in the United States. It is the gateway to care for a broad range of people, arriving from a variety of locations. With this wide reaching net and a decreasing trend in hospital beds, EDs throughout the United States are experiencing overcrowding. ED crowding has various tactical and strategic facility management impacts ranging from facility occupancy issues to adverse health outcomes. Among other factors, recent research has cited the sharp increase in ED visits over the years and ED patient boarding as key contributors to crowding.

Home hospital care is a model in which health care is delivered at an individual's home as a substitute for hospital-level inpatient short-term acute care. Clinical research has shown home hospital to be an effective care model for select illnesses presenting frequently to EDs, such as congestive heart failure, community acquired pneumonia, chronic obstructive pulmonary disease, and cellulitis. While there exist distinct clinical and social criteria for which delineate eligible individuals, home hospital care models have been linked with the potential to free inpatient beds.

The overarching objective of this study is to investigate the relationship between home hospital care and ED crowding. To achieve this objective, the study examined the relationship between home hospital care and ED crowding, specific to ED boarding performance at a large, urban, teaching hospital facility. A methodology for identification of potential home hospital patients was used through clinical and social criteria, and a scale for the range of clinical eligibility rates was established for the five suitable illnesses. The study modeled patient flow and bed demand, and utilized computer

simulation modeling to assess the impact of home hospital care on ED boarding performance. Various models were simulated to represent different home hospital intervention types. The models incorporated home hospital through an ED Referral program, Inpatient-Transfer Referral program, Community Referral program, and a fully integrated home hospital program. Three scenarios were run for each model to assess practical possibilities for the utilization of the freed bed hours from a home hospital program.

This research contributes insight and understanding of home hospital's impacts on ED crowding. The insight from this study quantifies the effects of a home hospital program on ED boarding and inpatient bed demand. The modeling study is contributes an analytical understanding of the impacts that home hospital could potentially have on crowding, which could prove useful in the struggle against ED congestion. This understanding helps to provide a more thorough understanding of home hospital, and could aid in an organization's decision-making process of whether to implement a program. The presented modeling methodology for analyzing home hospital and ED crowding can also be used as a model format for researchers and practitioners for analytical purposes in future studies.

CHAPTER 1

INTRODUCTION

The hospital emergency department (ED) is a critical source for health care amid a complex healthcare system in the United States (U.S.). It is a resource of health care for a broad range of people, arriving from a variety of locations. With this wide reaching net and a downward trend in available ED beds, hospital EDs in the United States are experiencing increases in crowding (Bair, Song et al. 2010, Hing and Bhuiya 2012). ED crowding has various tactical and strategic facility management impacts ranging from adverse health outcomes to facility occupancy issues. A significant amount of attention and time have been spent on the ED crowding crisis over the last two decades (Powell, Khare et al. 2012). There have been many proposed methods to solve or lessen crowding, each focusing on a variety of causes of crowding and each with varying degrees of success and limitations for hospital facilities. Recent research has determined that ED patient boarding is a major source of ED crowding. Meanwhile in non-crowding related research, home hospital care models have been linked with the potential to free inpatient beds. The research in this study sets out to explore the relationship between home hospital care and emergency department crowding, and to understand the impact that home hospital may have on crowding.

The healthcare sector is a broad and complex industry in the U.S. For the scope of this study, the terms, hospital and healthcare facility, will refer to an acute care hospital facility that services an emergency department located in the U.S. Hospitals are widely considered one of the most complex organizations to manage (Lavy and Fernández-Solis 2010). On an industry-wide level, national and local governments institute rules and guidelines for patient care, monetary reimbursements, facility management, and construction, among other issues. Further complexities arise at the

facility level, where hospitals bring together multiple and widely ranging services, employees, and customers. Hospital organizations vary in the types of services and treatments that they offer. Therefore the various departments that make up one hospital can vary from another hospital. In particular, the ED is considered the gateway to care for the community, as it is a major source for patients to enter a hospital and receive care. The ED could serve as a source of care for a community, city, or even an entire region. These facilities are used for a variety of care treatments, ranging from emergency trauma care to the common cold. Therefore depending on the size and resources of the hospital, many ED facilities are made up of multiple divisions or areas for the various patient types.

EDs are widely known as the safety net of the U.S. healthcare system (Hoot and Aronsky 2008). In 1986, the U.S. Congress enacted the Emergency Medical Treatment and Active Labor Act, which ensures emergency medical care to any person. With this wide reaching net and the obligation to treat all incoming patients, hospital EDs in the United States are seeing increasing numbers of patients over the years. According to an annual American Hospital Association survey, hospital ED visits per facility almost doubled from 18,300 visits in 1990 to 34,600 visits in 2011 (Martin 2013). More recently between 1999 and 2009, the number of ED visits increased 32% from 102.8 million visits per year to 136.1 million visits (Hing and Bhuiya 2012). The Institute of Medicine has cited the increase in ED visit volume as a principle cause for ED overcrowding in addition to hospital closures, financial pressures, and operational inefficiencies (Barrett, Ford et al. 2012). Further with the prevalence of chronic diseases and the aging U.S. population, high demand for care services is expected. Over 90% of people over 65 years of age have at least one chronic condition and 70% have two or more (Landers 2010). By the year 2030, over 70 million people in the U.S. are expected to be over 65. ED crowding and the resulting capacity-constrained facilities are not a problem specific to a certain region or demographic, but is widely considered a national crisis (Hoot and

Aronsky 2006, Powell, Khare et al. 2012). A significant amount of attention has been focused on capacity-constrained and crowded ED models for academic research purposes of U.S. hospitals. However crowding is still a national challenge that requires more study to alleviate the growing national crisis that is brewing (Warden, Griffin et al. 2006, Bair, Song et al. 2010, Powell, Khare et al. 2012).

Hospitals are expensive facilities to build, operate, and maintain. Depending on where they are located and the services and equipment they are prepared for, estimates for construction can be in the range of about one million dollars per bed (Kirby and Kjesbo 2003, Litvak and Bisognano 2011). Operating costs per bed can vary considerably, but can be in the neighborhood of \$250,000 per year (Litvak 2010). Making matters worse, hospitals are vulnerable to increasing financial pressure as Medicare, Medicaid, and perhaps even private payment rates are expected to drop due to the Affordable Care Act, and as hospital organizations may also have increasing difficulty borrowing money in capital markets (Litvak and Bisognano 2011). So when it seems a hospital is constrained on capacity, costly facility expansion is often not the first option or most preferred solution. Research has also focused on strategies that have potential to reduce crowding without costly capital projects. This is the light in which home hospital is to be considered for this study. The terms, home hospital, hospital at home, home care, remote hospital care, and remote care, will be used interchangeably in this paper to represent health care delivered at an individual's home as a substitute for hospital-level inpatient short-term acute care. If an individual is able to receive health care using existing resources without physically being present in the hospital facility, home hospital care could potentially be an alternative to counter shortages of beds and help reduce ED crowding. This study seeks to explore and understand remote hospital care's impacts on ED facility performance with respect to crowding. Recent studies in the U.S. have shown remote health care can be a viable model for certain care treatments and services. Further study is warranted to analytically assess if and how remote care can

translate into a positive impact on ED crowding in the case that hospitals are experiencing crowding and shortages of beds.

Motivation and Impact

In the healthcare industry, research often is directed at health care quality, patient care and satisfaction, cost of care, and staffing. However research regarding the hospital facility or facility management is also an important perspective to consider. Much like information technology, human resources, and finance divisions, facility management (FM) also works as a support function to promote and achieve an organization's goals. The motivation for home care research and growth is driven by five major forces: the aging U.S. population, epidemics of chronic diseases, technological advances in equipment and information technologies, healthcare consumerism, and skyrocketing healthcare costs (Landers 2010). However, existing home hospital care research lacks formal study of its impact on hospital facility management. To initiate this scope of home hospital research, the relationship between home hospital care and ED crowding can be investigated and analyzed, due to ED crowding's adverse impacts on FM issues. ED crowding, which is a widespread problem and is expected to grow worse (McNaughton, Self et al. 2012), impacts the hospital facility in a number of adverse ways with respect to the facility and managing the facility. From a FM perspective, two of the major categories which FM activities can be broken up into are strategic activities and tactical activities (Langston and Lauge-Kristensen 2002). Strategic FM typically relates to high-level corporate goals and planning. These strategic activities are implemented to work towards achieving the organization's long-term goals. Tactical FM activities are more concentrated in scope, and are aimed at helping an organization function and operate at a desired level of performance.

ED crowding can adversely impact strategic level FM on the basis of long-term uses of the facility. As crowding increases, the overall responsibility of the hospital to be

able to adequately care for the general public might be vulnerable. When ED crowding is present, often hospitals turn to diversion where ambulances are turned away and directed to find an alternate facility to treat the individual (Draper, Rosenberg et al. 2011). These actions can raise questions as to whether the hospital is able to uphold its responsibility to meet the capacity needs of the community both currently and in the future. ED crowding may trigger and impact boardroom-level discussions concerning occupancy rate concerns, capacity, and growth of the facility. Strategic FM discussions regarding expansion and other capital projects of the facility can be influenced or motivated by ED crowding. Crowding has also been shown to adversely impact the financial health of hospital organizations through opportunity costs and inefficient use of resources (Hoot and Aronsky 2008). Hospitals that see high and frequent levels of crowding should attempt to strategically prepare for the organizations' long-term viability.

From the tactical FM perspective, ED crowding can have numerous impacts on whether hospital facilities or staff working within a facility perform at desired levels or not. Previous research has shown that crowding can adversely affect access to care for individuals. ED crowding causes longer wait times for people to obtain care, and disrupts the operation of emergency medical services (Hoot and Aronsky 2006). Wait times in U.S. EDs have been getting progressively worse. Between 2003 and 2009, the median wait time to see a physician, physician assistant, or nurse practitioner increased 22%, from 27 minutes to 33 minutes (Hing and Bhuiya 2012). The mean wait time for the same period increased 25%, from 46.5 to 58.1 minutes. Similarly there are consequences for access to care when ED crowding causes ambulance diversion. Diversion can cause delayed patient transport to a treatment facility, which causes prolonged time to a care provider (Hoot and Aronsky 2008). In 2008, the mean wait time for treatment was 32% longer for EDs which were on ambulance diversion versus those which were not, statistically significantly different at 64.3 minutes versus 48.7 minutes respectively (Hing and Bhuiya 2012). Crowding also can lead to patient elopement in which individuals

leave hospitals without receiving treatment due to long wait times (Hoot and Aronsky 2008, McNaughton, Self et al. 2012).

ED crowding can also cause tactical FM impacts on quality of care performance levels. Hospital organizations want to maintain an acceptable quality of provided care, but past research has indicated that crowding affects this performance in undesirable ways. Crowding has been shown to cause adverse outcomes for patients with respect to patient mortality and increased hospital length of stay (Cameron 2006, Hoot and Aronsky 2008, McNaughton, Self et al. 2012, 2013). It has also reduced quality of care in terms of increased risk of medical error, treatment delays, unnecessary procedures, extended pain in patients, and low patient satisfaction levels. Additionally, ED crowding creates an atmosphere of disorganization, chaos, and lack of comfort, which can lead to unsafe conditions for patients, such as with elderly or disabled patients, people experiencing sleep deprivation, patients waiting on gurneys in hallways, etc. (Cameron 2006, Powell, Khare et al. 2012).

ED crowding research has also shown that crowding has undesirable effects regarding a hospital organization's financial issues. Crowding leads to substantial opportunity costs for the ED, as lost revenue is apparent when crowding has triggered ambulance diversion or patient boarding actions (Bayley, Schwartz et al. 2005, Hoot and Aronsky 2006, Hoot and Aronsky 2008).

With all the attention ED crowding has garnered through the years, it has certainly produced a variety of short-term and long-term solutions and fixes. Nevertheless, crowding remains a significant problem moving forward. ED crowding continues to garner and require further research as the healthcare community is still working to understand the interrelationships and interdependencies of the hospital system.

State of Knowledge

The body of knowledge regarding the impact of remote care on ED crowding is preliminary and speculative. However a great deal of attention has been directed at remote care and ED crowding independently. Remote care research regarding home care has various realms and is growing. Previous research has focused on defining home care and the various uses and impacts it can have on hospital facilities. Home care models include community-based schemes as well as hospital-resourced schemes, and have aimed at preventing or delaying nursing home admissions and preventing hospitalizations. However this study will focus its scope on home care that acts as a substitute for inpatient hospital-level care. The following terms will be used interchangeably to represent this type of home care for the remainder of this paper: home hospital, hospital at home, home care, remote hospital care, and remote care. Modern home hospital care research in the U.S. has grown over the last two decades, mainly stemming from a study by Leff et al. (1997) at Johns Hopkins University in which illnesses and criteria were identified to be suitable for remote hospital care. Most studies since then have assessed remote care for its quality of care, safety, clinical processes, satisfaction of care, functional status, and cost of care versus traditional hospital facility care (Leff, Burton et al. 1999, Leff, Burton et al. 2005, Aimonino Ricauda, Tibaldi et al. 2008, Mader, Medcraft et al. 2008, Leff, Burton et al. 2009, Shepperd, Doll et al. 2009a). Over the years, home hospital research has grown to include wider age ranges for participants and a larger variety of suitable illnesses.

Past research of ED crowding has focused on how to define and measure crowding, as there is not a uniform definition or measure which all hospitals use (Bernstein, Verghese et al. 2003, Weiss, Derlet et al. 2004). Past definitions often have looked at individual factors, such as ED diversion hours, ED occupancy rate, and patient boarding times (Weiss, Ernst et al. 2006). Recent research has developed more comprehensive and integrated measures that combine multiple factors, such as ED treatment spaces, ED staffing, patient volume, patient acuity, and hospital occupancy,

among other variables (McCarthy, Aronsky et al. 2008). Integrated measures of crowding, such as the NEDOCS and EDWIN scores, allow a standardized approach where levels can be compared across multiple facilities, and where a better understanding of causes, characteristics, and outcomes of crowding would be achievable (Weiss, Ernst et al. 2006). Researchers have also developed a number of different conceptual models to represent and better understand ED process and flow. Asplin, Magid et al. (2003) propose a model for ED crowding based on queuing theory and compartmentalizing ED functions into inputs, throughputs, and outputs as seen in Figure 1. Models, such as this, help researchers gain a better familiarity with ED crowding. Further, often causes and solutions to ED crowding can be described within the input-throughput-output framework.

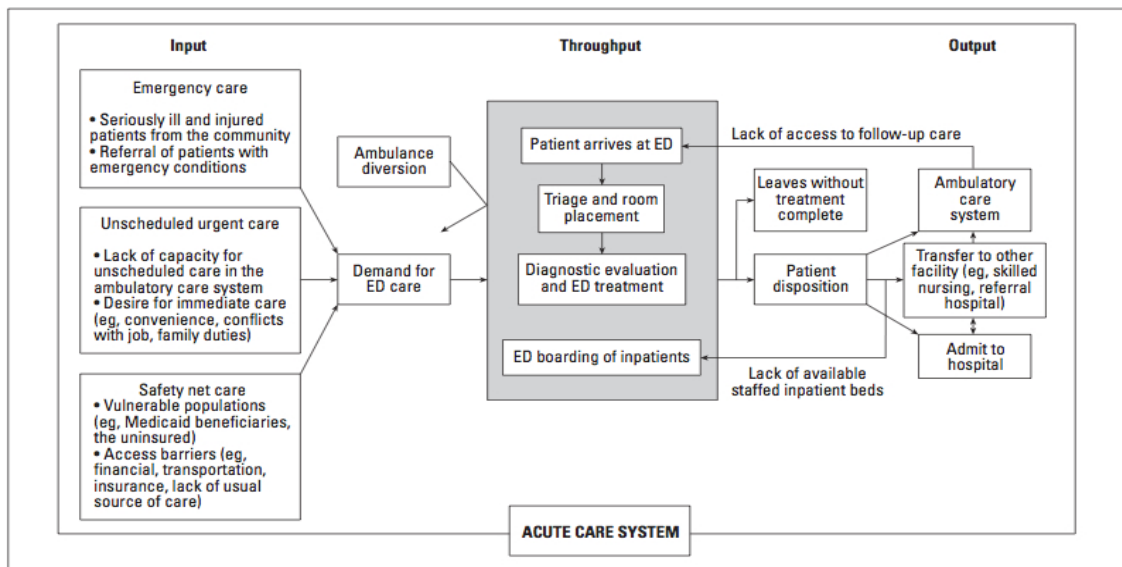


Figure 1 Input-Throughput-Output framework for ED crowding (Source: Asplin, Magid et al. (2003))

Prior research of ED crowding has worked to determine causes for crowding. Many of the causes can be framed within the input, throughput, and output factors outlined in Figure 1. Past research has found that input factors related to crowding include nonurgent ED visits, frequent-flyer ED patients, flu season patients, primary care access, and natural fluctuations in ED demand (Solberg, Asplin et al. 2003, Hoot and

Aronsky 2008). Throughput factors involve the efficiency of how the ED copes with and cares for patients. A significant indicator is the availability of ED beds for new patients (Solberg, Asplin et al. 2003, Hoot and Aronsky 2008, McNaughton, Self et al. 2012). Other throughput factors include inadequate ED staffing, increasingly extensive therapy in EDs, operational costs, and hospital restructuring limitations (Solberg, Asplin et al. 2003). Output factors relate to issues occurring outside the ED and yet still impact crowding within the ED. These factors include hospital bed shortages, the management of inpatient beds, scheduling practices of elective surgeries, and how well a hospital system is able to admit ED patients into inpatient wards (Solberg, Asplin et al. 2003, Hoot and Aronsky 2008, McNaughton, Self et al. 2012, Powell, Khare et al. 2012).

Much of the research directed at ED crowding in the 1980s and 1990s focused on the many patients seeking treatment for non-urgent medical conditions. Researchers and hospital organizations believed that significant factors of ED crowding were unnecessary ED visits and the patients who frequent EDs regularly (Viccielio 2008). However more recent research has shown little evidence to show that non-urgent patients independently have a significant impact on causing crowding (Dent, Phillips et al. 2003, Afilalo, Marinovich et al. 2004, Sprivulis, Grainger et al. 2005, Schull, Kiss et al. 2007, Hoot and Aronsky 2008). In its place, recent research has highlighted the significance of output factors and the management of hospital departments outside the ED as keys to ED crowding. Research has identified the key source contributing to crowding as ED patient boarding, described as ED patients that have been initially treated, an ED physician has made the decision to admit the patient, but the patient must wait for an inpatient bed to become available in order to be physically admitted to the hospital (Solberg, Asplin et al. 2003, Hoot and Aronsky 2008, Viccielio 2008, Powell, Khare et al. 2012). A Government Accounting Office study revealed that 90 percent of hospitals in the U.S. boarded patients for at least two hours, and that 20 percent of these hospitals operated with an eight hour average boarding time. As widespread as it is, ED boarding has been

linked to treatment delays, reduced quality of care, increased risk of medical error, increased hospital length of stay, more patients leaving without having been treated, and decreased patient satisfaction (Bair, Song et al. 2010, McNaughton, Self et al. 2012). Khanna et al. (2012) found that ED patient boarding is significantly higher on days which a hospital experiences higher occupancy. Further, correlations have been established between ED length of stay and hospital occupancy (Forster, Stiell et al. 2003, Cooke, Wilson et al. 2004). ED boarding is now considered the most significant and number one cause for ED crowding in hospital facilities (Viccielio 2008, GAO 2010).

Gaps in Knowledge

Existing literature lacks a formal study of the relationship between home hospital care and ED crowding. The relationship between these two disciplines has not been studied, and beyond speculation and presumption, there is no formal understanding. Home hospital research has not been directed at facility management issues, or more specifically ED crowding. To improve upon the present state of knowledge regarding home hospital and ED crowding, additional study must address the limitations that existing research heed. These limitations are discussed as follows.

Further Understanding the Relationship between ED Crowding and the Rest of the Hospital

Further research is necessary to uncover how ED crowding is related to the hospital system as a whole. Relationships between the ED and the rest of the hospital are not fully understood, and research is still surfacing these relationships (Shi, Chou et al. 2012). Researchers believe that advancements in crowding research would develop from more studies that analyze the ED within the integrated processes of a hospital, and even outside a single facility reaching out to community networks (Hoot and Aronsky 2008).

Output factors from Asplin, Magid, et al.'s ED Crowding model in Figure 1 have been highlighted by recent research as major sources of ED crowding. In 2006, the Institute of Medicine cited ED patient boarding as the most common cause of ED crowding, the Government Accounting Office has cited boarding as the single greatest cause of crowding, and ED crowding research has been called upon to incorporate a hospital system-wide approach (Warden, Griffin et al. 2006, GAO 2010, Barrett, Ford et al. 2012).

Relationship between Home Hospital and ED Crowding

Existing research lacks formal research directed at understanding the relationship between home hospital and ED crowding, as these two disciplines have not been studied together. While considerable attention has been given to home care research, previous studies fail to explore the connection between home hospital care and emergency department crowding, or other facility management issues. Although speculative assertions, presumptions, and broad statements regarding home hospital's ability to decrease admissions and free inpatient beds have been published, formal studies to assess the impacts to FM issues such as ED crowding have not been conducted (Cooke, Fisher et al. 2004). Therefore an analytical understanding of home hospital's impacts on ED crowding is missing. The level of influence or rate of impact has not been investigated and is not known.

Modeling Approach to Investigate the Relationship

As the relationship between home hospital and ED crowding has not been studied in past research, there has been no modeling approach presented to investigate the impact. There are numerous approaches for studying ED crowding, however they fall short of being able to analyze this relationship between home hospital and crowding. No

ED crowding models have incorporated home hospital impacts. No methodologies have been presented on how to address home hospital patients and where to integrate home hospital interventions into an ED crowding model. Development of an appropriate modeling approach is needed to investigate home hospital's impact on ED crowding.

Research Objectives

The overarching objective of this study is to gain insight into how home hospital care impacts ED crowding. The research aims to establish and assess the relationship to gain an analytical understanding of how remote care could affect crowding. The insight will aim to help hospitals better understand how home hospital programs are related to emergency department crowding via the integrated nature between the ED and the hospital system as a whole. To encompass this interface between the ED and the hospital, the primary performance measure used to evaluate ED crowding is ED patient boarding (see glossary). ED boarding is considered the most significant and number one cause for ED crowding, and is prevalent throughout hospitals around the country (Viccielio 2008, GAO 2010). While the scope of the study does not involve development of a decision support system for hospital organizations, this research acts as a foundation and starting point for future research to possibly build potential decision models from. Furthermore, the understanding and insight from this study could help management make an informed, comprehensive decision when determining how to improve ED crowding levels, or when considering implementation of a home hospital program. Although the study is based on extensive empirical study of one American hospital, the study and modeling approach is believed to be adaptable to other hospitals based on similar empirical observations at other facilities. The detailed objectives for this study are lined out below.

1. Establish crowding points of analysis from integration of home hospital care with ED boarding and hospital patient flow.

2. Develop a modeling approach to assess the impact of home hospital care on ED boarding for a hospital facility.
3. Apply the proposed modeling approach to various home hospital and hospital organization scenarios to investigate the relationship.

CHAPTER 2

LITERATURE REVIEW

The literature presented in this section represents the foundation upon which this study is developed. The literature review introduces concepts of facility management and discusses the association with ED crowding. An overview of the field of ED crowding research is presented. The scope of home hospital care is defined and described.

Facility Management

Facility management (FM) is a multidisciplinary field of work ensuring functionality and satisfaction of the built environment (IFMA 2013). The discipline can involve the integration of people, facilities, operations, and technology. Many definitions have been concocted to describe FM. As one of the early definitions from 1983, the U.S. Library of Congress states FM to be: “the practice of coordinating the physical workplace with the people and work of the organization; integrates the principles of business information, architecture and the behavioral and engineering sciences” (Chanter and Swallow 2008). The British Institute of Facilities Management adopts the definition for FM from the European Committee for Standardization as “the integration of processes within an organization to maintain and develop the agreed services which support and improve the effectiveness of its primary activities” (BIFM 2013). While such a broad and different range of businesses, facilities, and types of people exist around the world, FM can take on seemingly endless roles and responsibilities (Then and Chau 2012). So the scope of FM can vary from organization to organization, and from country to country.

The FM industry is gradually expanding and has been moving towards servicing the business, and not just the business’ real estate. Many corporations are aware of the value of facility management and the associated occupancy costs (Then and Chau 2012). While staffing costs often can represent up to 80 percent to 90 percent of an

organization's total expenditures, costs of facilities are often the 2nd largest expenditure (Langston and Lauge-Kristensen 2002). FM is being expected or is seeking to be aligned with company goals and needs. FM is expected to understand the core business of the organization, in order to help improve productivity, revenue generating capacity, and even the image of the company (Jensen, Voordt et al. 2012). Globalization of markets, new and advanced technology, and intensified competition have led businesses to try to get the most out of the resources they have access to. The FM field has been making a conscious effort to develop from being known as a trade industry to being perceived as an educated, scientific, and analytical field.

Strategic, Tactical, and Operational FM Activities

Langston and Lauge-Kristensen (2002) break FM activities into the three categories of strategic, tactical and operational level issues. Strategic FM typically relates to high-level corporate goals and planning. These strategic activities are implemented to work towards achieving the organization's long term goals. The strategic level activities could incorporate planning for growth and expansion, positioning the organization to enjoy competitive advantages over others, and establishing revenue-maximizing policies. Strategic FM benefits from the view of real estate facilities as resources towards achieving business goals (Then and Chau 2012). ED crowding can impact strategic level FM on the basis of long term uses of the facility. As crowding increases, the overall responsibility of the hospital to be able to adequately care for the general public might be vulnerable. When ED crowding is present, often hospitals turn to diversion where ambulances are turned away and directed to find an alternate facility to treat the individual (Draper, Rosenberg et al. 2011). These actions can raise questions as to whether the hospital is able to meet the capacity needs of the community currently and in the future. Therefore crowding may trigger and impact boardroom-level discussions concerning occupancy, capacity, and growth of the facility. Hospitals that see high and

frequent levels of crowding should attempt to strategically prepare for the organizations' long term viability. ED crowding research has also shown that crowding has undesirable effects regarding a hospital organization's financial goals. Crowding can lead to substantial opportunity costs for the ED, as lost revenue is apparent when crowding has triggered ambulance diversion or patient boarding actions (Bayley, Schwartz et al. 2005, Hoot and Aronsky 2006, Hoot and Aronsky 2008).

Tactical FM activities are more reduced in scope, and are aimed at helping an organization function and operate at a desired level of performance. Organizations have goals for how they want the facility to run and perform. Through organizational planning, FM associates should help achieve these levels of performance on a consistent basis. Tactical FM issues can also involve management of processes and support services. From the tactical FM perspective, ED crowding can have numerous impacts on whether hospital facilities perform at desired levels or not. Previous research has shown that crowding can adversely affect access to care for individuals. ED crowding causes longer wait times for people to obtain care, and disrupts the operation of emergency medical services (Hoot and Aronsky 2006). Similarly there are consequences for access to care when ED crowding causes ambulance diversion. Diversion can cause delayed patient transport to a treatment facility, which causes prolonged time to a care provider (Hoot and Aronsky 2008). Crowding also can lead to patient elopement in which individuals leave hospitals without receiving treatment due to long wait times (Hoot and Aronsky 2008, McNaughton, Self et al. 2012). ED crowding can also cause tactical FM impacts on quality of care performance levels. Hospital organizations want to maintain an acceptable quality of provided care, but past research has indicated that crowding affects this performance in undesirable ways. Crowding has been shown to cause adverse outcomes for patients with respect to patient mortality and increased hospital length of stay (Cameron 2006, Hoot and Aronsky 2008, McNaughton, Self et al. 2012, 2013). It has also reduced quality of care in terms of increased risk of medical error, treatment

delays, unnecessary procedures, extended pain in patients, and low patient satisfaction levels (Hoot and Aronsky 2006, Hoot and Aronsky 2008, McNaughton, Self et al. 2012, Powell, Khare et al. 2012, 2013). Additionally, ED crowding creates an atmosphere of disorganization, chaos, and lack of comfort, which can lead to unsafe conditions for patients, such as with elderly or disabled patients, people experiencing sleep deprivation, patients waiting on gurneys in hallways, etc. (Cameron 2006, Powell, Khare et al. 2012).

Operational FM deals with short-term and routine management activities that keep the facility running. These activities can involve maintenance of the facility, repairs, security, and gardening, among others.

Healthcare Facility Management

Healthcare facility management (HFM) has been a growing field, and has had an increasing effect on the quality and effectiveness of health care services. HFM is considered a significant factor in the successful delivery of health care (Shohet and Lavy 2004). Gallagher (1998) asserts that successful delivery is connected with the following major areas of HFM: strategic planning, customer care, market testing, benchmarking, staff development, and environmental management. Nonetheless, facility managers are often not involved in board or executive level planning and design, cost analysis, and performance and goal-setting meetings (Rees 1997).

Future Facility Management Research

As organizations and researchers have become more aware of the value of FM over the years, research has also progressed. FM research is evolving into the realms of corporate and social responsibility, where the industry is concerned with real estate, people, sustainability, and profits. The future of FM research will likely address these issues. A study conducted by the Centre of Facilities Management and Technical University of Denmark ranked the top two initiatives considered to be the highest priority

for the development of FM and for the importance of academic research involved: (1) introducing methodologies for FM to be a critical strategic management tool to connect with the business's core strategy; (2) to come up with tools or methods to document or measure the added value of FM services (Jensen, Voordt et al. 2012). Pullen et al. (2009) assert that the most significant future FM research actions to focus on involve the relationship between FM and corporate real estate management, sustainability, and strategy and added value. The last of which should work to reverse the idea of FM as a cost center, and look to explore how FM can add value to a company's goals. Similarly, two items on the 2015 International FM Research and Action Agenda are: (1) to explore how FM can contribute to a company's strategic objectives and to its competitive advantage over others; (2) to explore how FM can help to support people, the planet, and profit (Pullen, van der Voordt et al. 2009).

Emergency Department Crowding

Introduction of the ED and ED Crowding

The healthcare sector is a broad and complex industry in the U.S. For the scope of this study and this literature review, the terms, hospital and healthcare facility, will refer to an acute care hospital facility that services an emergency department located in the U.S. Hospitals are widely considered one of the most complex organizations to manage (Lavy and Fernández-Solis 2010). On an industry-wide level, national and local governments institute rules and guidelines for patient care, monetary reimbursements, facility management, and construction, among other issues. Further complexities arise at the facility level, where hospitals bring together multiple and widely ranging services, employees, and customers. Hospital organizations vary in the types of services and treatments that they offer. Therefore the departments that make up one hospital can vary from another hospital. Some common departments include the ED, the intensive care

unit (ICU), surgery units, cardiology, neurology, obstetrics, and oncology. In particular, the ED is considered the gateway to care for the community, as it is a major source for patients to enter a hospital and receive care. The ED could serve as a source of care for a community, city, or even an entire region. These facilities are used for a variety of care treatments, ranging from emergency trauma care to the common cold. Therefore depending on the size and resources of the hospital, many ED facilities are made up of multiple divisions or areas for the various patient types. Among the various divisions, often many facilities will have triage areas, resuscitation areas, acute care areas, prompt or urgent care areas, observation units, and psychiatric rooms.

EDs are widely known as the safety net of the U.S. healthcare system (Hoot and Aronsky 2008). In 1986, the U.S. Congress enacted the Emergency Medical Treatment and Active Labor Act which ensures emergency medical care to any person at all Medicare participating hospitals with emergency departments (Liu 2010). The law guarantees an appropriate medical screening exam and health stabilization treatment before transfer to another facility or discharge for any person regardless of ability to pay, immigration or citizenship status, or any other characteristic. With this wide reaching net and the obligation to treat all incoming patients, hospital EDs in the United States are seeing increasing numbers of patients over the years and crowding is putting a strain on EDs across the nation. According to an annual American Hospital Association survey, hospital ED visits per facility almost doubled from 18,300 visits in 1990 to 34,600 visits in 2011 (Martin 2013). More recently between 1999 and 2009, the number of ED visits increased 32 percent from 102.8 million visits per year to 136.1 million visits (Hing and Bhuiya 2012). The Institute of Medicine has cited the principle causes for ED overcrowding as the increase in ED visit volume, along with hospital closures, financial pressures, and operational inefficiencies (Barrett, Ford et al. 2012). ED crowding and the resulting capacity-constrained facilities are not a problem specific to a certain region or demographic, but is widely considered a national problem (Hoot and Aronsky 2006,

Powell, Khare et al. 2012). In 2009, 78% of ED visits occurred in facilities that reported ED patient boarding in hallways or other spaces (Hing and Bhuiya 2012). A significant amount of attention has been focused on capacity-constrained and crowded ED models for academic research purposes of U.S. hospitals (Hoot and Aronsky 2008). However crowding is still a national challenge that requires more study to alleviate the growing national crisis that is brewing (Warden, Griffin et al. 2006).

Defining ED Crowding

Emergency department crowding can mean different things to different people or organizations. There is no uniform definition that is used across all organizations or facilities (Bernstein, Verghese et al. 2003, Weiss, Derlet et al. 2004). The lack of a consistent and generalizable definition makes comparing ED crowding difficult from facility to facility. Often definitions look only at certain factors, such as diversion hours or ED occupancy rate, or they focus on factors outside the ED itself, which makes crowding measures hard to standardize across various facilities since many have differing challenges and conditions (Weiss, Ernst et al. 2006). Having a more consistent, standardized, and uniform approach to measuring ED crowding would allow for a better understanding of causes, characteristics, and outcomes of crowding.

The American College of Emergency Physicians defines ED crowding as: “a situation in which the identified need for emergency services outstrips available resources in the ED. This situation occurs in hospital EDs when there are more patients than staffed ED treatment beds and wait times exceed a reasonable period. Crowding typically involves patients being monitored in non-treatment areas (e.g. hallways) awaiting ED treatment beds or inpatient beds. Crowding may also involve an inability to appropriately triage patients, with large numbers of patients in the ED waiting area of any triage assessment category” (Case, Fite et al. 2004). Others take a simpler approach to describing the term. Some care organizations define ED crowding as when the ED is on

ambulance diversion (Bernstein, Verghese et al. 2003). Ambulance diversion is described as when hospitals request that ambulances avoid their ED and instead transport patients to other care facilities. Experts have noted that diversion can be a useful measure of crowding particularly for urban hospitals, as they are more likely to be located nearby other hospitals where patients can receive care (Solberg, Asplin et al. 2003). Another proxy used to characterize ED crowding is ED patient boarding. Boarding can be defined as when a patient remains in the ED after the decision to admit or transfer the individual is made by a caregiver (Hing and Bhuiya 2012). Boarding often occurs when an inpatient bed elsewhere in the hospital is not available for the ED patient. Some organizations feel ED crowding does not exist until boarding has transpired for more than six hours per day (Derlet, Richards et al. 2001). Others have defined crowding with simpler proxies such as once daily ED visit totals reach a certain number, once ED beds are filled for more than a particular number of hours per day, if patients wait more than one hour to see a physician, or if a the waiting room is filled for more than a certain number of hours (Derlet, Richards et al. 2001, Bernstein, Verghese et al. 2003).

Causes of ED Crowding

Researchers and practitioners present numerous causes for ED crowding. This is likely a testament to the fact that not just one issue is the single factor. Further, these causes for crowding can occur within different realms of ED operations. Asplin, Magid, et al. (2003) present a commonly cited conceptual model of ED crowding, as seen in Figure 1. The model is split up between input, throughput, and output factors. With various factors that can cause crowding, certain factors will assuredly be more influential than others.

Input Factors

Input factors denote the arrival of patients to the ED. This patient flow is a function of how many people are ill and injured in a community, and can also be dependent on the community's health care system and its ability to care for the individuals not requiring emergency care (Solberg, Asplin et al. 2003). Over the last few decades in the U.S., the volume of ED visits has grown substantially. In the 1960s, American hospitals were largely places for elective admissions or scheduled surgeries, with only a small fraction of patients being unscheduled emergency patients. However over the years, crowding has grown with changing healthcare policies, sicker populations, and sharp rises in the number of unscheduled emergency visits and hospital admissions (Vicciello 2008). Between 1990 and 2011, hospital ED visits almost doubled from 18,300 to 34,600 (Martin 2013). Hospitals saw a significant rise in visits after the Emergency Medical Treatment and Labor Act of 1986, which forced hospital EDs to administer a medical screening examination to any and all patients who go to US hospitals, regardless of ability to pay (Hoot and Aronsky 2008). Experts are not exactly sure how the recently passed Affordable Care Act will affect ED visits, as an expected 32 million additional Americans will become newly insured (Peters and Dean 2011). It waits to be seen how this group uses health care services, whether within the primary care sector or at hospital facilities.

A long-time studied input factor of ED crowding has been non-urgent patient visits to the ED. These visits often represent low-acuity patients visiting due to inadequate access to primary care or simply untimely or difficulty in obtaining timely access to primary care (Hoot and Aronsky 2008). Frequent-flyer patients are another input factor group that has been studied. In a study by Huang, Tsai, et al. (2003), frequent visitors, referred to as those with four or more ED visits per year, made up 14 percent of all ED visits. In a similar study, the 500 most frequent visitors accounted for 8 percent of all ED visits, and it was determined that 29 percent of the visits may have been treatable through primary care (Dent, Phillips et al. 2003). Other input factors that can

cause crowding are flu season, or on the other hand natural fluctuations or random surges in patient demand (Solberg, Asplin et al. 2003, Hoot and Aronsky 2008).

Throughput Factors

Throughput factors of ED crowding relate to bottlenecks occurring within the ED. Throughput factors depend on the efficiency of the ED and how well it can cope with the input of patient demand (Solberg, Asplin et al. 2003). Factors range from the supply of beds and staffing to the efficiency of administrative management and efficiency of ancillary services.

Clearly the scarcity of ED beds adversely affects crowding. As the number of ED visits has been rising over the years, the stock of ED beds has been shrinking at the same time (McNaughton, Self et al. 2012). With bed supply down, hospitals have turned to assigning patients to nontraditional beds, such as gurneys in hallways and conference rooms. Even with traditional beds, inadequate staffing in EDs, particularly with nursing shortages, also affects throughput (Solberg, Asplin et al. 2003, Hoot and Aronsky 2008). Increasingly extensive therapy in EDs is also impacting crowding (Solberg, Asplin et al. 2003). Caregivers are spending more time with patients in the ED than before. Increased operational costs of care and any sort of ongoing hospital restructuring also take its toll on crowding. When a facility is being renovated, expanded, or just reorganized, operational capacity may be compromised.

Output Factors

Output factors that can contribute to ED crowding refer to bottlenecks outside the ED. Factors include how well the hospital system admits ED patients requiring inpatient care, and the ambulatory care system's ability to provide timely post-discharge care (Solberg, Asplin et al. 2003). It has become increasingly apparent from recent research that these issues influence the ED a great deal. Inpatient hospital factors, such as elective

surgeries, inpatient bed management, and facility occupancy rates, can affect ED crowding. Powell, Khare, et al.'s work (2012) suggests a correlation exists between rising hospital occupancy and increasing ED length of stay.

When a hospital reaches high levels of inpatient occupancy, it becomes difficult to place incoming patients into beds. ED patients are often the individuals forced to wait for an inpatient bed to become available. This in turn backs up the ED, and makes it harder to admit new patients to the ED (Solberg, Asplin et al. 2003, Hoot and Aronsky 2006, McNaughton, Self et al. 2012). This combination of events is referred to as ED patient boarding. Much of the research directed at ED crowding in the 1980s and 1990s focused on the many patients seeking treatment for nonurgent medical conditions. It was believed that this was the root cause for when EDs were full and having trouble giving care (Viccellio 2008). Much of this research focused on retrospective views of emergency patients after diagnoses were given. From this perspective, it was easy to say that many of the ED visits were unnecessary for what turned out to be nonurgent medical conditions. However more recent research claims that many of these nonurgent patients do not know if their conditions are emergent or not. If a child has a fever, he/she could simply have a cold or could have severe meningitis. It would feel the same to the child, and so the ED visit is not necessarily unwarranted or excessive. This same wave of recent research over the last decade or so has focused on ED patient boarding as a key cause to ED crowding (Solberg, Asplin et al. 2003, Viccellio 2008). The U.S. General Accounting Office conducted a two year study in which ED patient boarding was the factor most commonly attributed with crowding (GAO 2003). Similarly, Powell, Khare, et al. (2012) found that the most significant bottleneck to the ED is the rate at which admitted ED patients leave the ED for inpatient beds. They concluded that if this rate were improved, it would have a more significant impact on decreasing ED length of stay than adding ED beds. Bair et al. (2010) provide a quantification of the impact that boarding has on ED crowding using a discrete event simulation study. They conclude

that eliminating boarding completely could decrease the amount of time an ED spends with an overcrowded NEDOCS score of over 100 from 88.4 percent to 50.4 percent. Eliminating boarding also would decrease the rate of patients who leave without being seen from 10.8 percent to 8.4 percent.

Causes of ED boarding clearly stem from other parts of the hospital outside the emergency department. ED patients are boarded when these other areas of the facility have no room or beds for the additional patients. So management of these beds becomes a significant issue. Khanna, Boyle et al. (2012) determined that patient boarding times, as well as length of stay durations, are significantly higher on days with higher hospital occupancy. The General Accounting Office (2003) study identified two principal causes associated with boarding to be: (1) hospitals are incentivized to only staff beds that will assuredly be occupied consistently, which makes the facility vulnerable to sudden surges in demand; (2) ED patients compete for inpatient beds with other admission sources which typically generate higher revenue streams. The financial impacts on hospital staff efficiency relate to the fact that hospital organizations generally aim to staff beds that will be occupied. So in times of high demand for care, the facility may be undermanned and vulnerable to untimely service rates. These consequences then can lead to an inability to admit patients from the ED. The revenue issue stems from the fact that the hospital system may prefer to admit other sources of inpatient admissions, such as elective surgeries or cardiac catheterization, over ED admissions due to the often higher profit margins.

Effects of ED Crowding

ED crowding can affect various organizational goals, performance metrics, and operational processes in a hospital. Research has shown that reduced quality of care is associated with overcrowding, causing increased hospital length of stays, decreased patient satisfaction, transport delays, treatment delays, increased risk of medical error,

and adverse outcomes such as patient mortality (Hoot and Aronsky 2008, Liu, Chang et al. 2011, McNaughton, Self et al. 2012, Powell, Khare et al. 2012). ED crowding can also clearly impair access to care for individuals. This leads to the obstruction of delivery of emergency medical services and causes ambulance diversion (Hoot and Aronsky 2008). Further, decreases in access to care lead to patient elopement, where individuals leave without being cared for or before care is complete (Hoot and Aronsky 2008, McNaughton, Self et al. 2012). The chaotic and congested scenes spawned by ED crowding can also lead to unsafe conditions regarding patient safety, particularly with elderly, disabled, or sleep deprived patients waiting on gurneys or in crowded hallways (Cameron 2006, Powell, Khare et al. 2012).

ED crowding has also been shown to affect hospital provider financial loss, as opportunity costs exist (Bayley, Schwartz et al. 2005, Hoot and Aronsky 2006). If the ED is crowded and cannot receive more arrivals, ambulances are unable to unload patients promptly or are forced to deliver individuals to other organizations (Hoot and Aronsky 2008). Bayley, Schwartz, et al. (2005) estimate a hospital lost \$204 per chest pain patient in potential revenue due to lengthy boarding times of greater than three hours. This resulted in an annual opportunity cost of \$168,300. People often believe that boarding leads to maximizing revenue due to the fact that non-ED admissions typically have higher reimbursement rates. But Pines, Batt, et al. (2011) analyzed an inner city teaching hospital and found that reducing boarding times and occasionally reducing non-ED admissions is a financially attractive strategy.

Measuring ED Crowding

Just as there are numerous definitions for ED crowding, there are also an assortment of metrics used to measure crowding. Past studies have used logical and easily accessible metrics to assess ED crowding levels. These metrics have included ED length of stay (LOS), ED LOS for admitted patients, the time it takes for individuals to be

seen by a provider, and staff perceptions of crowding. Past studies have also used calculable expressions such as ED occupancy to represent crowding levels. The data elements needed to compute ED occupancy are total number of patients present in the ED including the waiting room and the number of available and staffed ED treatment areas (Solberg, Asplin et al. 2003, McCarthy, Aronsky et al. 2008). The expression is as follows:

$$ED\ occupancy = \frac{(total\ number\ ED\ patients\ registered)}{(total\ number\ staff\ ed\ ED\ treatment\ areas)}$$

Based on 74 experts' opinions, ED occupancy was rated as 82.2 percent more useful than a standard measure to be used for clinical and administrative operations, as well as 70.5 percent more useful for researching the causes and consequences of ED crowding (Solberg, Asplin et al. 2003). This method can easily be tracked real-time, since most EDs manage patient registrations and discharges electronically, and because the number of treatment bays is known (McCarthy, Aronsky et al. 2008).

Besides single properties or common metrics, ED crowding measurement instruments have integrated a variety of operational factors together to develop comprehensive crowding assessments. Examples of incorporated factors are ED staffing, ED treatment spaces, patient volume, patient acuity, equipment usage, and hospital occupancy (McCarthy, Aronsky et al. 2008). These scoring methods make crowding rates reproducible and thus comparable to other EDs. However they can be laborious or unsuitable for real-time tracking of crowdedness since many EDs do not have electronic patient tracking systems that automatically collect the data necessary to calculate the scores.

One such standard for a multi-factor crowding measurement is the National Emergency Department Overcrowding Scale, otherwise known as NEDOCS. NEDOCS was developed to be a simple tool to objectively evaluate the level of crowding in a hospital ED (Weiss, Derlet et al. 2004). The tool aims to allow various facilities to

compare crowding measures and impacts to crowding to each other by way of a standardized and objective definition or scale. Developers of the score used academic hospitals with high ED patient volumes to test and validate the scale. Development was directed to these facility types because they generally supply care for urban, indigent populations and they are often thought to be affected by overcrowding.

The score was developed by attempting to model the outcome variable of real-time expert opinions of ED crowding (Weiss, Ernst et al. 2006). Linear regression was used to relate operational variables to the level of crowdedness gauged by physicians and nurses (Hoot and Aronsky 2006). The NEDOCS formula calculates an EDs score at a particular point in time, and correlates with the facility's operational capacity at that given time. The seven variables used in the formula, seen below, are the number of ED beds, number of hospital beds, the number of ED patients, the number of ED admits, the number of ED respirators, longest admit time in hours, and the wait time for the last patient called from triage. The ED and hospital beds referred to refer to the budgeted number of beds available for patient care. Therefore nontraditional and temporary beds are not to be included. The number of ED patients refers to the total number of patients in the ED receiving care, regardless of whether the patients are located in normal, doubled-up, and hallway beds, or those receiving care in chairs, triage, or the waiting room. The number of ED respirators refers to the number of respirators or ventilators in use in the ED. The wait time for last patient called refers to the time in the waiting room for the last patient that was called to an ED bed.

$$NEDOCS = 85.8 \times \left(\frac{ED\ patients}{\#\ ED\ beds} \right) + 600 \times \left(\frac{ED\ admits}{\#\ hosp\ beds} \right) + 13.4 \times (\# \ ED\ respirators) \dots \\ + 0.93 \times (longest\ admit\ time) + 5.64 \times (wait\ time\ of\ last\ patient) - 20$$

Variable data entered into the algorithm yields a score between 1 and 200. An ED with a score less than 100 is considered not crowded. An ED with a score of equal to or greater than 100 is considered overcrowded. Within these scores, there are six categories or

levels of crowding: Not busy, Busy, Extremely Busy, Overcrowded, Severely Overcrowded, and Dangerously Overcrowded.

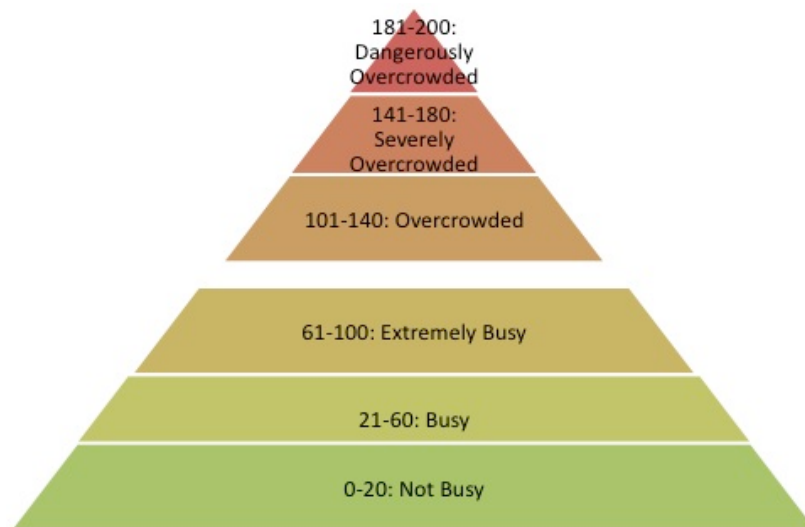


Figure 2 NEDOCS score rubric

NEDOCS studies have validated the score and show that it correlates well with expert opinion on ED crowding levels. Weiss et al. (2006) show NEDOCS to correlate well with a standardized ED overcrowding outcome variable based on physicians and the ED charge nurse opinions. NEDOCS has also been shown to exhibit very good sensitivity for crowding.

Solutions for ED Crowding

For the last two decades, researchers have focused a great deal on ED crowding and solutions to the problem. Some have helped reduce crowding for particular facilities, while others have not.

Increasing resources of the facility or organization is an often attempted and studied crowding solution type. Often expansions of facilities and the addition of ED beds are used to reduce ED congestion, as reports have indicated that lack ED beds has led many hospitals to using nontraditional patient evaluation areas such as gurneys in hallways, conference rooms, and waiting rooms (McNaughton, Self et al. 2012). While increasing space and numbers of beds has shown to improve certain crowding outcomes,

they often work with limited benefits as bottlenecks tend reappear. The additions of observation units can also be used to improve crowding performance, as these divisions of the ED allow a place for the care of patients requiring brief stays in the hospital (Hoot and Aronsky 2008). Efforts to reduce crowding have also looked at increasing staffing of caregivers, and increasing the stock of medical equipment to be able to do things like lab testing at the point of care in the ED.

Past research has also considered demand management techniques for improving ED crowding. Reduction of nonurgent referrals has been studied, while being a controversial issue (Afilalo, Marinovich et al. 2004). There is a cloud of uncertainty and lack of knowledge as to who these patients are and what the impact might be on the healthcare system if they are turned away from the ED and referred to wait until they can access primary care. Regardless, recent research has deemed nonurgent referrals as a less significant key to crowding as was once perceived (Hoot and Aronsky 2008). Other demand management techniques to reduce crowding are using paramedic-initiated transport control and ambulance diversion. With paramedic-initiated transport control, the paramedics assess the individual at the site and decide whether the individual warrants an ED visit or not. Ambulance diversion is the act of bypassing a particular ED due to overcrowding and taking the individual to another facility for care. There are also community outreach care coordination programs that have been studied and implemented to manage demand at EDs. These social interventions typically aim to service frequent ED visitors using counseling, education, or ongoing coordinated care to reduce readmissions (Draper, Rosenberg et al. 2011).

Operations and patient flow improvements are another group of ED crowding solutions. Discharge timing has been credited with potentially decreasing crowding with respect to bed management and throughput management (Barrett, Ford et al. 2012, Khanna, Boyle et al. 2012). Powell, Khare, et al. (2012) show that altering the elective surgical schedule of the hospital can significantly help to reduce crowding and patient

boarding in the ED. Their study demonstrated that shifting the peak discharge timing for the day to four hours earlier eliminated the need to board patients in the ED. If 75 percent of the patients were discharged before noon, boarding decreased from 77 to three hours per day. Khanna, Boyle, et al. (2012) studied 23 hospitals in Australia and found that discharging patients earlier would improve occupancy levels in the hospital, and also reduce ED patient boarding and ED LOS durations. ED crowding solutions such as discharge timing highlight the fact that ED patient flow is closely associated with external factors and a hospital-wide approach is required to solve the problem.

Home Hospital Care

Home Hospital Care Introduction and Scope

Home care is a loosely defined term in the literature. It includes home and community based services, adult day care, foster care, case management, and technology based automatic safety response systems (Hughes, Ulasevich et al. 1997). Models of home care can include high-technology home care, Medicare skilled home care, hospice care, or personal or homemaker care. With respect to this study, home hospital care will be limited in scope to refer to remote care for which would otherwise be given in a hospital facility. This version of home hospital began in 1961 in France, and was known as Hospitalisation a Domicile (Shepperd, Doll et al. 2009b). Care that was provided for select groups of patients who typically received care in a hospital. The health care was hospital-level care, including specialist care, for those individuals who opted to receive care in their home. The scope for home hospital within this study refers to health care delivered by a health care professional providing active, short-term acute care in an individual's home for treatment that would otherwise necessitate inpatient admission in an acute care hospital. The care is intended to be for a limited time; long term care is not included in this scope of home hospital. Further, the health care professional should take

an active part in caring for the patient; care is not intended to be self-care service or self-monitoring service.

Over the years, this model of home care has evolved to have various schemes or program types as home hospital has spread to the U.S., the United Kingdom, Australia, Japan, the Netherlands, and Italy. Home hospital programs may be hospital-resourced, where in-house hospital staff make home visits and deliver treatment. There are also community-based schemes, where care is outsourced to others outside the hospital. In the United Kingdom, the community-based schemes are more popular, as nurse-led home care agencies build on the primary care system. In the U.S. and Australia, the hospital-resourced schemes are more popular. Hospital admission is avoided or reduced through the establishment of a few different referral sources to home hospital. The home hospital ED Admit Model is when patients are evaluated in an ED facility and referred to home hospital; the Inpatient Transfer Model is when patients who have already admitted to inpatient beds are transferred to home hospital for the remainder of their care; patients may also be assessed in the community by primary care physicians or urgent care clinic physicians and referred to home hospital (Shepperd, Doll et al. 2009b).

Home hospital has been implemented and used by organizations and communities for various reasons. The American healthcare system has been battling with spiking health care costs for decades. The escalating costs of inpatient care have led to the exploration of cheaper substitutes (Hughes, Ulasevich et al. 1997). A goal for many homecare advocates is to cut costs by avoiding hospital admission (Shepperd, Doll et al. 2009a). Another reason for home hospital support and implementation is for hospitalists' desires to keep people out of hospital facilities in order to protect patient health. While people clearly enter hospitals to be cured or treated of illnesses, additional adverse effects, such as hospital-acquired infections, can be experienced once inside the hospital. This is particularly true for elderly populations. Additionally, home hospital is attractive with respect to the belief that patients also would prefer to stay in their homes and live

independently (Hughes, Ulasevich et al. 1997). Again this is particularly popular with elderly populations. The benefits of the home environment are enticing in some cases, as the perception tends to be that people can be more relaxed, comfortable, enjoy greater privacy, and control noise and light levels. Further, the advancement in the technology to treat people has spurred home hospital advocates as well (Hughes, Ulasevich et al. 1997).

Suitable Illnesses

In the U.S., much of the recent home hospital academic research has been initiated or developed from a study by Leff, Burton, et al. in 1997 (1997). This study identified eligible illnesses that would be suitable for home hospital care. The three illnesses identified were congestive heart failure (CHF), community acquired pneumonia (CAP), and chronic obstructive pulmonary disease (COPD). One of the reasons these illnesses were chosen, besides suitability for remote care, was that they also typically represent illnesses that account for substantial percentages of hospitalizations. In the year the study was conducted, these three illnesses accounted for 18.3 percent of all hospital discharges of person 65 years and older in the state of Maryland. Later research by Leff, Burton et al. (2005) added cellulitis as a suitable illness to be treated via remote hospital care as well. A study out of Presbyterian Healthcare Services in Albuquerque, New Mexico added deep venous thrombosis (DVT), pulmonary embolism, complicated urinary tract infection or urosepsis, nausea and vomiting, and dehydration (Cryer, Shannon et al. 2012). Illnesses that are not triaged as immediate or emergent will mainly be suitable for home hospital. A significant portion of ED patients are generally triaged in these categories. About 40 percent of individuals presenting to the ED are triaged as needing to be seen within 15–60 minutes, and referred to as urgent; about 35 percent are triaged as needing to be seen within 1–2 hours, known as semi-urgent; and about 7 percent of patients are triaged as needing to be seen between 2 and 24 hours, which is considered nonurgent (Hing and Bhuiya 2012). Private industry in the U.S. has approved

and completed treatment of suitable illnesses to be treated via home hospital, and is working to include other illnesses. The company, *Clinically Home*, has completed studies and as of October, 2013 is awaiting approval to include the following illnesses to be suitable for home hospital: hepatitis, seizures, pancreatitis, transient ischemic attack, GI maladies, syncope, vertigo, renal stones, pain syndromes, urgent hypertension or high blood pressure, wound care, sickle cell, Parkinsonism, diabetes mellitus, peritonitis, and sepsis. See Table 1 for a summary of suitable illnesses being treated via home hospital in the U.S.

Table 1 Illnesses judged as suitable for home hospital treatment in the U.S.

From Research Published in Peer-Reviewed Journal Articles	Pending Approval
Community Acquired Pneumonia	Hepatitis
Congestive Heart Failure	Seizures
Chronic Obstructive Pulmonary Disease	Pancreatitis
Cellulitis	Transient ischemic attack
Pulmonary Embolism	GI maladies
Deep Venous Thrombosis	Syncope
Urinary Tract Infection or Urosepsis	Vertigo
Nausea and Vomiting	Renal stones
Dehydration	Pain syndromes
Asthma	Urgent hypertension or high blood pressure
	Wound care
	Sickle cell
	Parkinsonism
	Diabetes mellitus
	Peritonitis
	Sepsis

Patient Eligibility Criteria

Beyond the illnesses that can be treated via remote hospital care, criteria for eligibility has also been established with respect to feasibility of each individual's situation and characteristics. Not all individuals with a potentially suitable illness for home hospital will be eligible for home care. Patients should not be so sick that they require an intensive care unit, but at the same time they should not be healthy enough that

they would not warrant an admission to the hospital in the first place. From the studies and programs that have been undertaken in the U.S., most follow very similar eligibility criteria. Many past studies and programs in the U.S. have based home hospital eligibility criteria on the validated clinical and social criteria from the Hospital at Home related studies initiated by Leff et al. at Johns Hopkins University (1997). The criteria are typically made up of clinical and social characteristics. The clinical criterion is a combination of an individual having a particular illness suitable for home hospital care, however while not possessing certain associated exclusionary medical characteristics. The exclusions are in place due to the fact that regardless of an illness being considered suitable for home hospital, there are varying levels of illness severity and necessary treatment levels, some of which may not allow for home hospital or would require treatment at a hospital facility. The social criteria for eligibility of home hospital generally includes age restrictions, the patient living in a stable and safe residence with adequate or basic utilities, and residing within a particular catchment area from the hospital ED. The initial study by Leff et al. (1997) called for inclusion criteria to correspond with individuals who match the following:

- Aged 65 years or older
- Live within 25 miles of and 35 minutes from the hospital
- Resides in a fixed, safe, and adequate residence with basic utilities

Other studies and existing home hospital programs have modified the age limit to include individuals aged 18 and older, while keeping the remaining criteria the same.

Quality of Care

The quality of care of home hospital has been researched using clinical trials in the U.S. The results are often positive. In a study of CHF patients, no significant differences were found between home hospital and traditional inpatients for comorbidity, functional status of individual, and health-related quality of life (Mendoza, Martín et al.

2009). Leff, Burton, et al.'s 2005 study (2005) found that home hospital patients had shorter length of stays and there was evidence of fewer complications. They also found that care process measures matched with inpatient care with respect to use of oxygen therapy, intravenous antibiotics, and nebulized bronchodilators. Shepperd, Doll, et al.'s (Shepperd, Doll et al. 2009a) meta-analysis of 10 trials of home hospital found that home hospital patients had significantly lower risk of death at six month follow-ups. However not all studies result in positive results for home hospital patients. Nevertheless, there are a handful of ongoing home hospital programs in the U.S. despite quality of care concerns and despite the challenging payment reimbursement mechanisms in the U.S. Based on existing literature as of October 2013, there are home hospital programs at the Portland Veterans Affairs Hospital, the Louisiana Veterans Affairs Hospital, Presbyterian Health Services in New Mexico, and at Centura in Colorado Springs.

CHAPTER 3

INTEGRATING HOME HOSPITAL CARE WITH ED BOARDING AND PATIENT FLOW

This chapter establishes and explains the aspects of ED crowding that are evaluated with respect to impacts from home hospital. These points of analysis will serve as the focus of the analysis efforts, which will then bring forth the results to assess the impact of home hospital on ED crowding. The following methodology is presented below to achieve the research objectives stated in Chapter 1.

1. Establish characterization of home hospital program's impact on hospital patient flow
2. Determine method for retrospective identification of potential home hospital patients
3. Develop simulation model representing hospital bed demand and ED crowding measures
4. Simulate various home hospital models to evaluate impact on ED crowding

Current literature regarding remote hospital care does not focus on its relationship with ED crowding, and similarly literature regarding ED crowding does not tend to incorporate remote hospital care. Many researchers and practitioners use an input-throughput-output framework to understand causes and potential solutions to ED crowding. While there are various models presented in the literature, Asplin, Magid et al. (2003) present a common and often cited model which is illustrated in Figure 1. Their input-throughput-output framework models patient flow among various sites of the acute care system with respect to ED crowding. Existing research has identified ED patient boarding as the key contributor towards ED crowding and therefore will be the primary outcome measure to represent ED crowding used in this study (Solberg, Asplin et al.

2003, Hoot and Aronsky 2008, Vicciello 2008, Powell, Khare et al. 2012). The input-throughput-output framework shows ED boarding in the throughput section, and research supports that a major factor contributing to boarding rates is a lack of staffed inpatient beds and inefficient patient admission (Asplin, Magid et al. 2003). Correspondingly, researchers have conceptually noted remote care's ability to free inpatient beds. Therefore this research focuses on home hospital's impact on ED boarding through the effects to inpatient capacity and timing of availability of beds. This section presents the characteristics of home hospital programs studied in this research, and establishes the manner in which a home hospital program may impact patient flow and ED boarding.

Characterization of Home Hospital

Many different forms of home hospital have been assessed over the years in the international literature. Examples include programs designed to act as substitutes for hospital treatment, avoidance of admissions models, programs aimed at early discharge, early discharge for ongoing rehabilitation, nursing home programs, and outpatient and physician office-based infusion centers, among others. This study focused its home hospital care research on clinically validated programs providing inpatient hospital-level treatments remotely in a patient's home. With various healthcare systems, reimbursement systems, and quality of care standards from one country to another, this study is focused on home hospital in the United States. In order to define the scope of remote hospital care for this study, the following definition is employed: active health care delivered by a professional at an individual's home that acts as a substitute for inpatient short-term acute care. The scope for home hospital within this study refers to health care delivered by a health care professional, such as physicians and nurses, providing active, short-term acute care in an individual's home for treatment that would otherwise necessitate inpatient admission in an acute care hospital. The care is intended to be for a limited time; long term care is not included in this scope of home hospital.

Further, the health care professional should take an active part in caring for the patient; care is not intended to be self-care service or self-monitoring service.

The home hospital program analyzed in this study is assumed to be hospital-resourced, where in-house hospital staff make home visits and deliver treatment. This program type is selected for study due to various factors. While community-based schemes are common in certain parts of the world such as the United Kingdom, in the United States, the hospital-resourced home hospital programs are more popular (Shepperd, Doll et al. 2009b). With the fee for service model functioning in the U.S., hospital organizations typically do not want to turn away patients and potential revenue. Also, a hospital-resourced home hospital program allows a hospital organization control over program decisions, such as capacity, schedules, investment, etc.

While there have been various home hospital programs studied and operated in the U.S. over the years, they have largely been modeled after a program developed at Johns Hopkins University (Leff 2009). Therefore, this study uses the Johns Hopkins “Hospital at Home” model of care as the implementation method for which remote care is studied in this investigation. Moreover just as the Hospital at Home model has evolved over the years, this study includes the added aspects of the evolutions of the program. The resulting models are labeled for the purposes of this study in terms of when or where the individual is referred or admitted to home hospital with respect to patient flow in the healthcare delivery process. Regarding this research, referral source to home hospital refers to the healthcare site at which a medical professional initiates the admission to home hospital for inpatient-level care. The home hospital models analyzed in this study are discussed as follows.

The home hospital ED Referral Model is based on the combination of the first Johns Hopkins model (Leff, Burton et al. 1999), subsequent evolutions such as the Presbyterian Healthcare program (Cryer, Shannon et al. 2012), and the private industry Clinically Home model (ClinicallyHome 2014), among others. These programs are

similar with respect to admission source to home hospital, program operations, and patient flow. The ED Referral Model is when an individual is admitted to home hospital from the ED healthcare facility; see Figure 3 for a summary of the home hospital emergency department referral model. The model begins with an individual requiring health care arriving to an emergency department. If ED staff identifies the patient as having a suitable home hospital illness and being a potential home hospital candidate, home hospital staff assesses the patient's eligibility for hospital at home. This screening process includes meeting certain clinical and social criteria, as discussed in the literature review above. Once the patient is deemed eligible and the patient consents to home hospital, the patient is transported home either by a friend or family member, contracted vendor or agency, or by an ambulance. Through vendor partners, the home is equipped and setup for home hospital needs, including the delivery and installation of any infusion equipment, oxygen therapy equipment, medications, diagnostic services and telehealth equipment, and other durable medical equipment. Once home, the patient is evaluated again by the hospital at home physician or nurse, and diagnostic and therapeutic measures are taken if applicable. The patient may receive direct nursing supervision for the initial portion of care, depending on the level of acuity of illness. Intermittent follow up visits are employed thereafter between one and three times per day by the nurse, or as needed to care for the patient. Care staff administer medications and infusions, perform routine lab tests, and teach the patient or family about managing the health condition. Physicians may visit patients daily for medical care, diagnosis, and care plan management. Additionally, telehealth services, such as blood pressure monitoring, stethoscopes, oximeters, glucometers, and video connections, can be used to further support monitoring of the patient for clinical changes in health. Diagnostic studies and tests are taken at home when possible for measures such as electrocardiograms, radiography, ultrasound, durable medical equipment, intravenous fluids, intravenous antimicrobials and other medicines, and respiratory therapies. Measures that cannot be provided at home, such as

computerized tomography, magnetic resonance imaging, and endoscopy, can be conducted via outpatient centers of the hospital. The patient is cared for and followed until stable and ready for discharge. A home hospital patient's readiness for discharge is determined using the same criteria as a hospital inpatient.

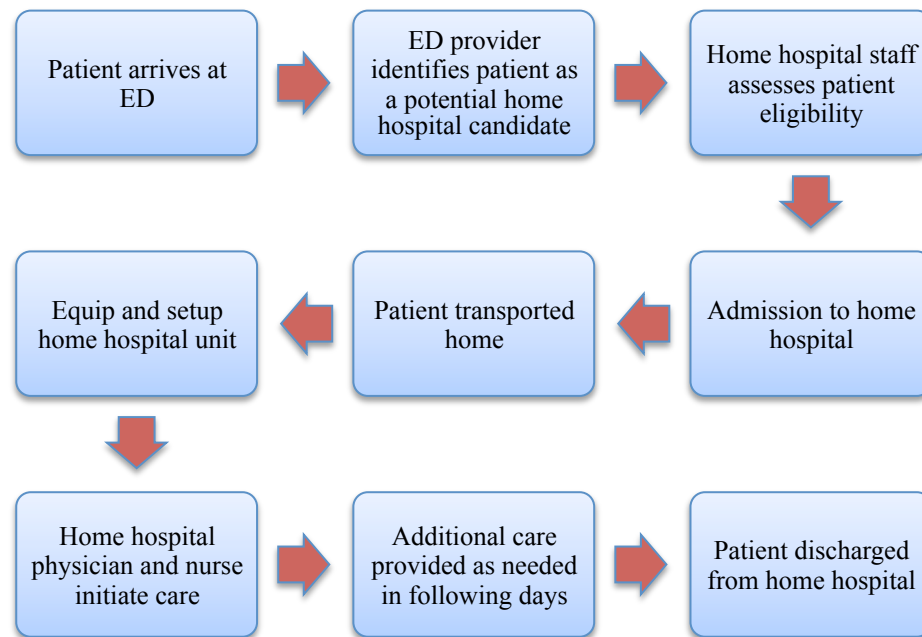


Figure 3 Summary of ED referral home hospital care model

Another evolution of the home hospital care model utilized in the U.S. is the Inpatient-Transfer Referral Model, such as employed at the Portland Veterans Affairs Medical Center, the Southeast Louisiana Veterans Affairs Healthcare System, and the Presbyterian Healthcare programs (Mader, Medcraft et al. 2008, Cryer, Shannon et al. 2012, 2013). The Inpatient-Transfer Model is different from the ED Referral Model in that the patient is first admitted to an inpatient bed, and then subsequently referred for transfer to a home hospital bed to complete the care. Figure 4 presents a summary of the inpatient-transfer referral care model and is explained as follows. An individual has been admitted to an inpatient bed. While the patient requires further hospital-level care, the individual is identified as having a suitable home hospital illness. A home hospital physician assesses the patient for home hospital eligibility regarding clinical and social criteria. If the patient is deemed eligible and the patient consents to home hospital, the

patient is transferred from the inpatient bed to a home hospital bed. The individual is transported home either by a friend or family member, contracted vendor or agency, or by an ambulance. Once the patient is home, care is administered until home hospital discharge in the same manner as the ED referral care model described above. The inpatient-transfer home hospital care model is used in a variety of scenarios. One such scenario is if a patient initially requires admission to an ICU bed, and then upon an improvement in health is transferred to a home hospital bed instead of transferring to an inpatient bed. Another scenario occurs when home hospital admission from the ED is not available at the time of requested admission, perhaps due to home hospital capacity limits in hours of operation or staff shortages. Therefore after initial inpatient admission, a patient can be transferred to home hospital once admission is an option.

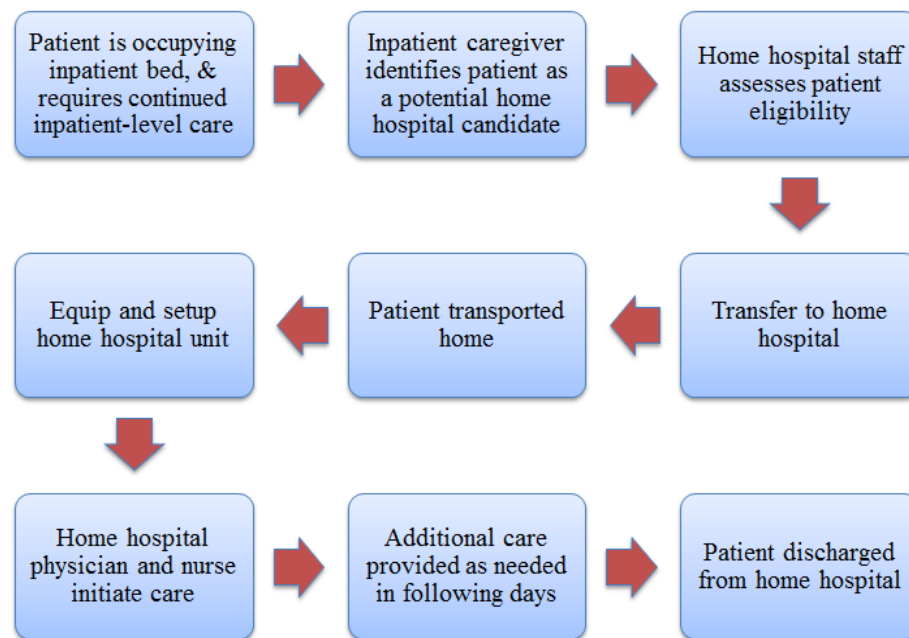


Figure 4 Summary of inpatient-transfer referral home hospital care model

A final home hospital care model to be studied in this research is the community referral model, as has been employed in the Presbyterian Healthcare program (Cryer, Shannon et al. 2012), Buffalo's Univera and Independent Health's programs, and Worcester's Fallon Health Care System's program (Leff, Burton et al. 2005). In this care model, the patient is referred to home hospital from a community site such as an urgent

care clinic, without ever presenting to the hospital. Figure 5 presents a summary of the community referral home hospital care model and is explained as follows. An individual presents to a healthcare site in the community other than a hospital for care, such as urgent care clinics, home health agencies, and primary and subspecialty clinics. Considering the caregiver determines that the patient requires hospital-level care, the individual is referred for home hospital based on having a suitable home hospital illness. Using patient medical records, home hospital staff assess whether the patient meets certain clinical and social criteria. Home hospital staff then assess the patient's medical eligibility for home hospital. Once the patient is deemed eligible and the patient consents to home hospital, the patient is transferred to a hospital at home bed, if transport is necessary. Once the patient is home, care is administered until home hospital discharge in the same manner as the ED and inpatient-transfer referral care models above.

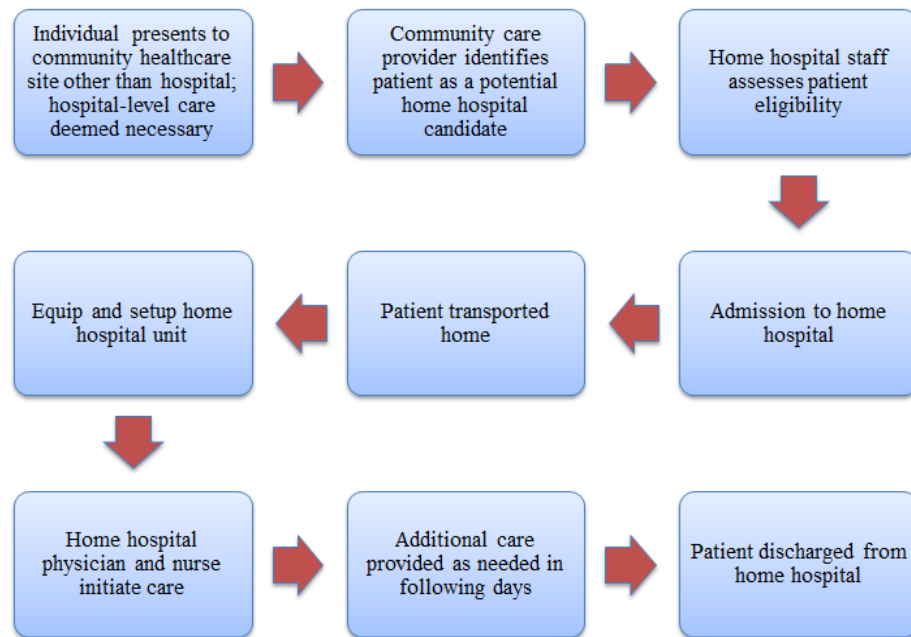


Figure 5 Summary of community referral home hospital care model

This research aims to study how home hospital care programs impact ED crowding within the scope of the care models described in this chapter. This section has characterized home hospital programs in order to set the parameters for the type of home hospital care model that is analyzed in this study.

Home Hospital Impacts on Output Component of ED Crowding

This section establishes the relationship between how remote hospital care integrates with output elements of ED crowding. The leading output component contributing to ED crowding concerns inefficient disposition of ED patients, which leads to ED patient boarding (Asplin, Magid et al. 2003). The management of elements outside the ED that impact the ability to move admitted ED patients to an inpatient bed are critical to keep the flow of patients moving for admission. ED patient boarding has been recognized as the most frequently cited reason for ED crowding (Derlet, Richards et al. 2001, Forster, Stiell et al. 2003, GAO 2003), regarded as the number one cause for ED crowding (Viccielio 2008), and has been determined to be the most significant factor for ambulance diversion (Schull, Lazier et al. 2003). Output factors contributing to ED patient boarding include a lack of physical inpatient beds, inadequate or inflexible nurse-to-patient ratios, inefficient care practices in inpatient units, and delays in discharging patients to post-acute care facilities (Asplin, Magid et al. 2003).

As a key output factor affecting ED boarding, availability of inpatient beds is studied in this research with respect to home hospital intervention. As existing research acknowledges home hospital's potential to increase patient capacity (Leff and Mader 2008), increasing bed capacity is expected to improve daily wait time performance (Shi, Chou et al. 2012). Home hospital's effect on bed availability is studied for changes to ED patient boarding rates with respect to hourly and daily timescales. Daily relationships between admissions and discharges are evaluated as patient lengths of stay are often over multiple days. Hourly relationships are also analyzed based on an hourly scale of arrivals versus discharges, and is influenced by the timing of when inpatient beds are made available in a given day.

Patient Flow Intervention from Home Hospital

This study analyzes how home hospital impacts ED boarding based on increased inpatient capacity. While home hospital does not increase the physical number of beds in a hospital facility, it may be a method to make more inpatient beds available to those who cannot receive remote care (Leff and Mader 2008). This result would be a perceived increase in patient capacity for which could receive care for the hospital. This section describes home hospital's effect on a patient's movement through a hospital system with respect to changes in bed availability. The typical current practice of patient flow from the ED through a hospital admission system is presented in Figure 6, and begins with a patient arriving to the ED. The patient is triaged and level of care required is determined. Typically once an ED bed is available, a caretaker examines the patient, orders any diagnostic testing or lab work to be conducted, and eventually diagnoses the patient (Khare, Powell et al. 2009). The patient is treated and the ED physician determines the disposition of the patient, for example discharge, admission to hospital, transfer to another facility, patient observation unit, etc. Once ED care is complete, the patient's disposition is carried out. If admission is necessary, the ED staff files necessary documentation and submits a request for an inpatient bed assignment. When a bed is available, the patient is transported to the inpatient ward and is cared for by hospital staff, thus occupying and utilizing a bed from the inpatient capacity.

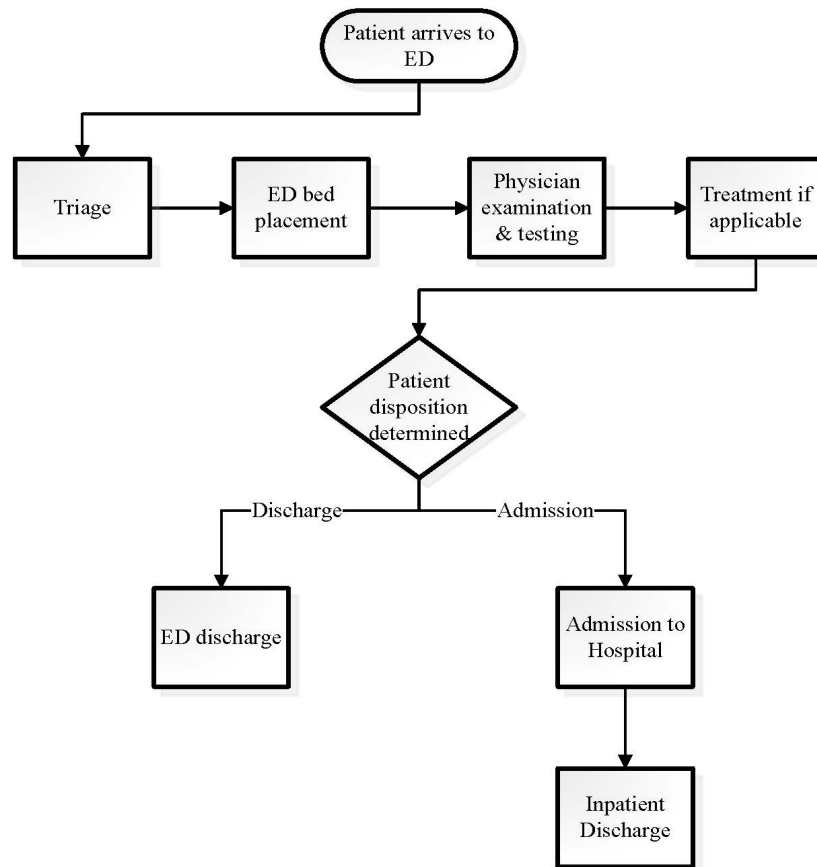


Figure 6 ED to hospital patient flow in current practice

As discussed above, home hospital as studied in this research can have multiple referral sources. Therefore home hospital can impact patient flow in multiple ways. The ED referral model has the potential to alter the course of the current patient flow practice at the point at which the ED physician determines the disposition of the patient. At this point, an alternative patient flow initiates due to home hospital. As can be seen in the ED referral model in Figure 3, if the patient is deemed eligible for home hospital care and if consent is granted, the hospital organization is able to provide care for the individual via home hospital services. Thus, a would-be inpatient admit can be cared for without occupying an inpatient bed, leaving the bed for an additional inpatient needing care (Leff and Mader 2008). Assuming a home hospital program in which care is provided by

hospital-sourced providers, this model allows the inpatient care capacity of the hospital to increase. This modified patient flow is diagrammed in Figure 7.

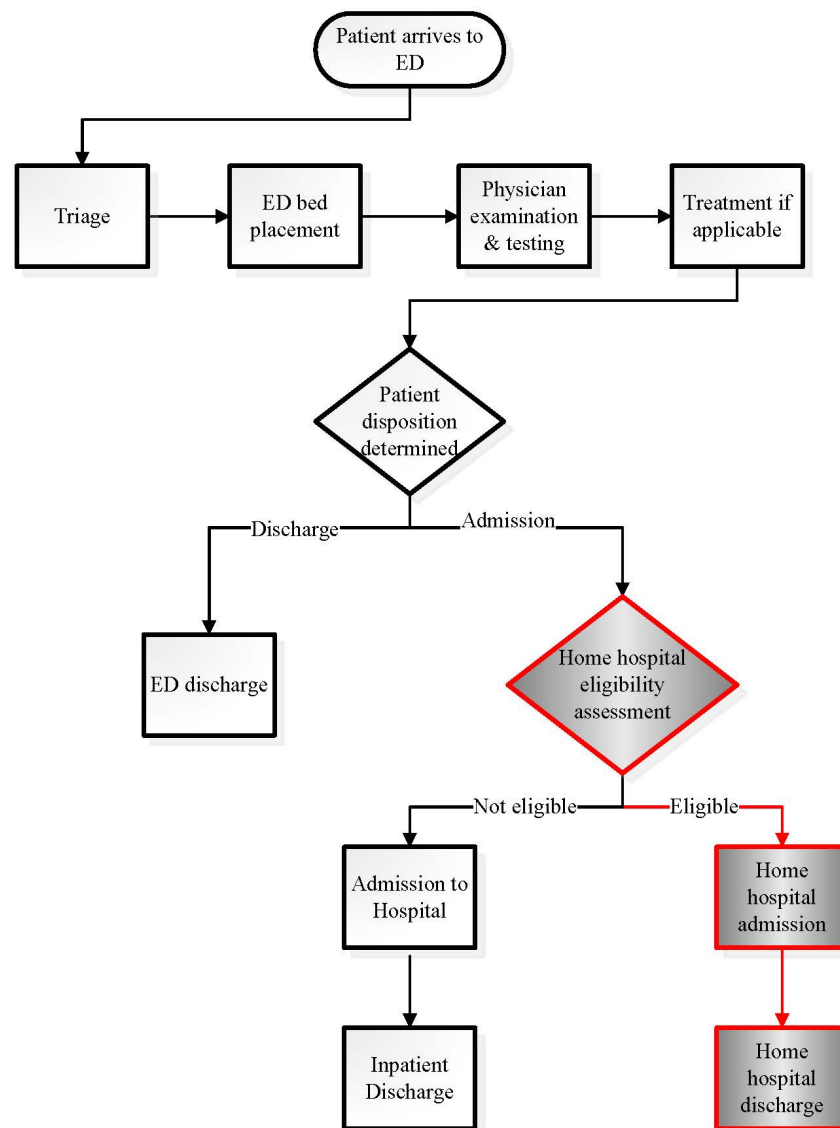


Figure 7 Patient flow intervention for home hospital ED referral model

The home hospital inpatient-transfer referral model, as described in Figure 4, also would alter patient flow to similarly increase inpatient-level care capacity. The inpatient-transfer referral model potentially alters the course of the current patient flow practice after admission to an inpatient bed has been completed. This modified patient flow is diagrammed in Figure 8. At this point, an alternative patient flow initiates due to home

hospital. As can be seen in the diagram, if the patient is deemed eligible for home hospital care and if consent is granted, the patient is transferred to a home hospital bed and provided care via home hospital services. Thus, an inpatient admit can be cared for while spending less time occupying an inpatient bed. Once the inpatient is transferred to a home bed, the bed is available earlier for a new inpatient needing care.

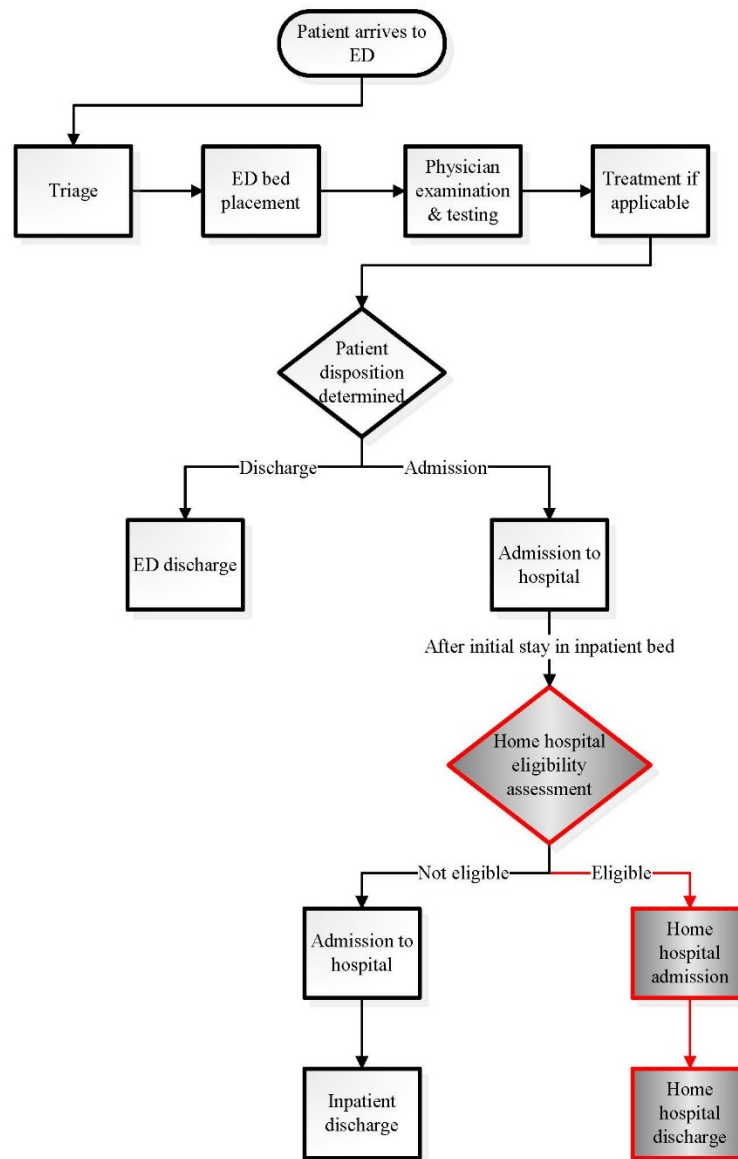


Figure 8 Patient flow intervention for home hospital inpatient-transfer referral model

The Community Referral model has the potential to alter the course of the current patient flow practice at the point at which the patient enters the hospital system. At this

referral source, an alternative patient flow can potentially initiate due to home hospital. As can be seen in the Community Referral model in Figure 5, as the patient presents to a community healthcare site, such as a physician's office or community clinic, the patient is assessed for home hospital eligibility. If deemed eligible and if consent is granted, the patient is directed home and the care is provided for the individual via home hospital services. Thus, the patient would not present to the hospital facility for admission, and could be cared for without occupying an inpatient bed while leaving the bed for an additional inpatient needing care (Leff and Mader 2008). This modified patient flow is diagrammed in Figure 9.

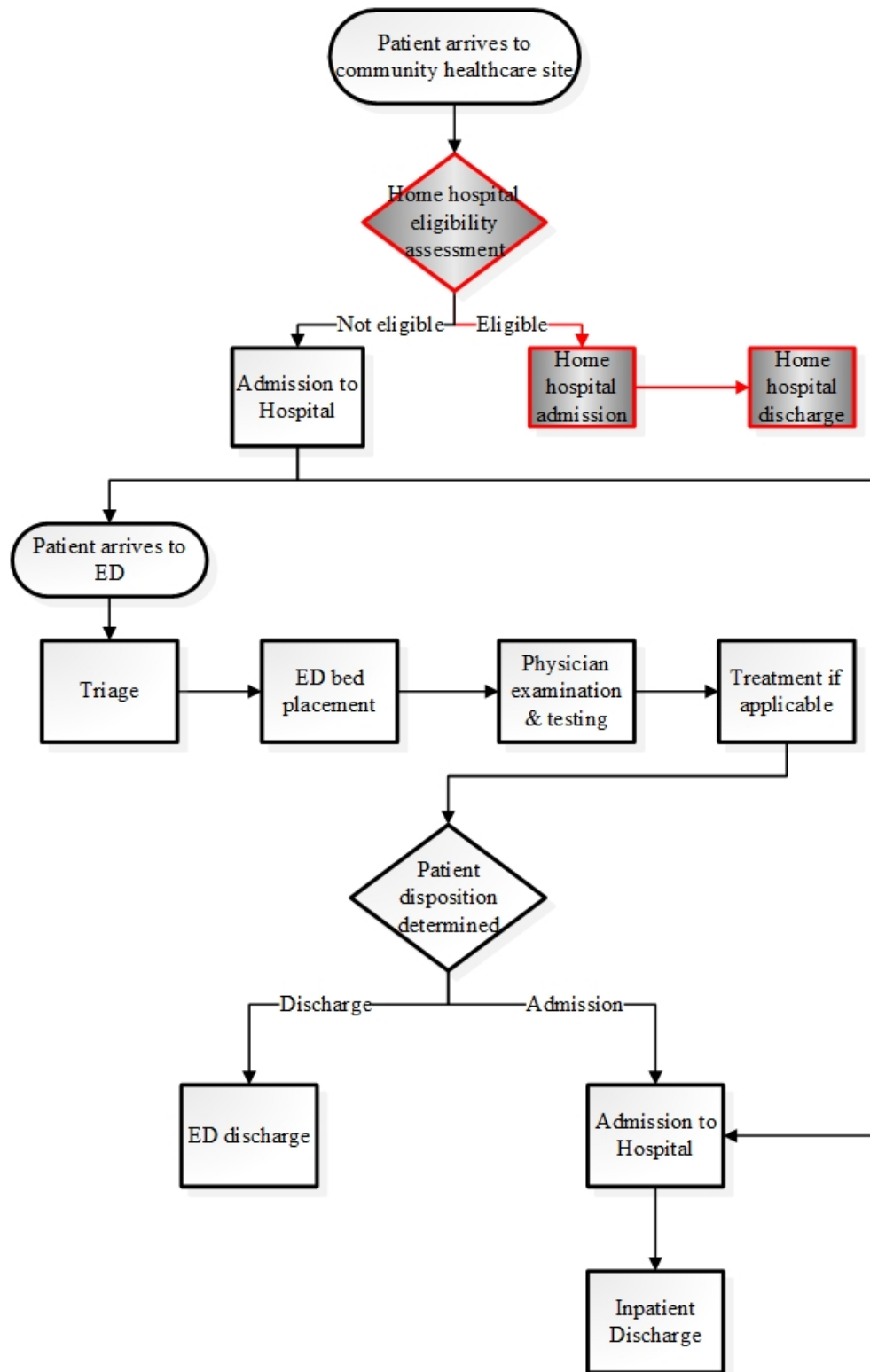


Figure 9 Patient flow intervention for home hospital community referral model

CHAPTER 4

MODELING APPROACH TO ASSESS THE IMPACT OF HOME HOSPITAL CARE ON ED BOARDING

The previous section sets out to explore relationships and associations between remote hospital care and ED crowding. In turn, this section establishes a modeling approach to assess the impact that remote care has on ED crowding for a hospital facility. This model is based on and developed within the integration of home hospital care and ED crowding. The following steps are completed to develop the modeling approach.

ED Intervention Opportunities

The relationship between remote hospital care and ED crowding discussed in Chapter 3 presents intervention opportunities where remote hospital care may influence typical ED patient flow. The intervention opportunities are characterized as referral sources for patients to home hospital, representing how and where an individual is may be identified as a home hospital care patient. Types of remote hospital care referral sources from past studies and programs are reviewed to determine when home hospital care can be implemented for specified patient targets. The anticipated home hospital admission opportunities are: referrals in the ED, transfers from the inpatient hospital ward to home hospital, and admissions from the outside community directly to home hospital. These intervention opportunities are used in the modeling approach as the areas for which to study home hospital's impact on ED crowding.

Remote Hospital Care Targets

While not all illnesses people present to hospitals with are treatable by remote hospital care, there are validated and verified diagnoses that have been deemed suitable. Through the review of remote hospital care studies in the US, this research identifies

patient targets to focus on for home hospital intervention actions. These patient targets represent the individuals that remote hospital care could be suitable for. Without any intervention of hospital operations, these patients would be treated per the status quo. But in this research study, location of care for these patients is altered via the implementation of remote hospital care. This section reviews past medical research to identify suitable illnesses for homecare. Targeted illnesses are characterized as illnesses that an individual's ED physician or primary care physician feels inpatient treatment is required, but that homecare can be conducted as a substitute given the appropriate caregivers, services, and equipment and materials are provided.

In this research, illnesses that have been validated to be suitable for home hospital in American studies are included for analysis. The illnesses have been verified for suitability in refereed journals and/or are currently being treated in existing home hospital programs in the U.S. Validation of suitability for home hospital in refereed journal articles is accepted for those illnesses which final conclusion in the discussion areas claimed home hospital to be a satisfactory option for care. While there were multiple studies evaluating the same illnesses, and not all medical results were exactly the same as others, this study accepts an illness to be a home hospital target diagnosis if the authors' consensus was to accept home hospital as a viable medium for care. Further validation is rooted in the fact that the illnesses evaluated in this study that are deemed as appropriate target illnesses are all in current, existing home hospital practices (K. Jenkins, personal communication, August 8, 2013, L. Kawasaki, personal communication, August 15, 2013, K. Thompson, personal communication, April 22, 2014). Limiting the number of potential illnesses to be treated via home hospital limits the number of patients that can be impacted, which allows for a conservative approach to determining impacts to ED crowding.

In U.S. studies, present-day home hospital research and programs began with verifying the suitability of four common illnesses: community acquired pneumonia

(CAP), congestive heart failure (CHF), chronic obstructive pulmonary disease (COPD), and cellulitis. Leff, Burton, et al. (1997) began verifying these four illnesses in their work, as they make up a considerable portion of ED admissions to American hospitals. Ensuing American studies and existing programs continued treatment of these four illnesses (Leff, Burton et al. 2005, Mader, Medcraft et al. 2008, Cryer, Shannon et al. 2012, 2013), while evaluating and validating various other illnesses for home hospital (Cryer, Shannon et al. 2012). Other illnesses verified in past research studies and being treated in existing home hospital programs in the U.S. include deep vein thrombosis (DVT), pulmonary embolism, urinary tract infection or urosepsis, nausea and vomiting, and dehydration. In 2003, CAP, CHF, and chronic obstructive lung disease were the first, second, and sixth most frequent conditions admitted to U.S. hospitals through the ED, respectively (Elixhauser and Owens 2006). These three conditions accounted for 13.4 percent of all cases admitted through the ED. When accounting for the other groups of conditions that include additional suitable home hospital illnesses, such as fluid and electrolyte disorders, urinary infections, and skin infections, these condition groups accounted for 19.7 percent of admissions to the inpatient beds from the ED in 2003. Table 2 lists the illnesses targeted in this study for home hospital care.

Table 2 Target illnesses modeled for home hospital care intervention

From Research Published in Peer-Reviewed Journal Articles
Cellulitis
Chronic Obstructive Pulmonary Disease
Community Acquired Pneumonia
Congestive Heart Failure
Deep Venous Thrombosis

Eligibility of Remote Hospital Care Individuals

Although particular illnesses have been deemed suitable for home hospital through past medical research, not all individuals presenting with those illnesses are in fact eligible for home hospital. Patients presenting to a hospital with a suitable home

hospital illness can present with various levels of acuity. Different levels of severity of an illness can require various amounts of treatment or resources for care. Therefore while some patients with a suitable illness may be able to be admitted to a home hospital program, others may be required to be admitted to the traditional hospital facility. Often the reason that an individual may not be eligible for home hospital is due to the care provider deeming the individual a high-risk patient for remote care. High risk might refer to the individual's health deteriorating quickly and requiring urgent or timely care. High risk might also refer to a scenario when a physician is not confident in predicting how an individual's health may progress, and therefore may deem a patient unfit for home hospital.

Social Eligibility

Many past studies and programs in the U.S. have based home hospital eligibility criteria on the validated criteria from the Hospital at Home related studies initiated by Leff, Burton, et al. at Johns Hopkins University (1997). The criteria are typically made up of social and clinical characteristics. The social criteria for eligibility of home hospital typically includes age restrictions, patients living in a stable and safe residence with adequate or basic utilities, and residing within a particular catchment area from the hospital ED. The social criteria used in this study are discussed in the following commentary and is ultimately presented in Table 3 below.

Regarding age limitations, past studies have typically restricted care to adults, aged either 65 years and older or to all adults aged 18 years and older. In the U.S., earlier home hospital studies limited age to 65 and older, while more recent studies opened up care to adults 18 and older. No American studies were found to evaluate home hospital for children, and a limited number were found in international studies. As a wide age range for adults has proven feasible in the recent U.S. studies, this research evaluates adults aged 18 years and older.

Regarding the fixity and utilities required of residences, past studies have often only specifically called out utility needs. U.S. and international studies have explicitly called for landline telephone service. Determining whether a residence is a fixed, consistent, and safe domicile is often judged by either physical inspection of the residence during admission or by discovering illegal substances in the patient's system upon initial evaluation (L. Kawasaki, personal communication, August 15, 2013). Reports of specific criteria or rates regarding safe, fixed, and adequate residences have not been found in published studies; published articles have not been found to address this social criteria as a barrier to implementation for home hospital. Therefore in this study, it is assumed that patients who do not have means of providing payment or reimbursement for care at a hospital may fall into a category of patients living in a residence unsuitable for home hospital. In the U.S., the average rate of uncompensated care costs is about six percent of total costs (AHA 2014). Therefore this study assumes 94 percent of patients to live in a stable, safe, and adequate residence for home hospital.

The final social criterion for home hospital eligibility hinges on living within a certain catchment area from the hospital ED facility. U.S. Hospital at Home studies have set catchment areas to a radius of 25 miles or 35 minutes from the hospital ED. International studies similarly have set catchment areas ranging from a radius of 15 miles to broad metropolitan areas around the city which the hospital facility is located in. This study uses the catchment area applied in U.S. studies: 25 miles and 35 minutes from the hospital ED facility.

Table 3 Social Eligibility Criteria for Home Hospital

Social Characteristic/Criterion	Criterion Used in This Study
Qualified age range	18 years and older
Living within catchment area	25 miles
Living in fixed and safe residence with basic utilities	94% of patients

Clinical Eligibility

This study required an appropriate method for determining clinical eligibility rates for home hospital care so as to be able to model its impact on the hospital facility. The eligibility rates are instrumental in determining what portion of a hospital's patient population may be affected by remote care. Clinical eligibility criteria are a combination of meeting certain inclusionary and exclusionary criteria. The clinical inclusion criteria consist of an individual presenting with a target illness suitable for home hospital care and requiring hospital admission for care if home hospital is not an option. Clinical exclusion criteria are in place due to the fact that regardless of an illness being considered suitable for home hospital, there are varying levels of illness severity and necessary treatment levels, some of which may not allow for home hospital or would require treatment at a hospital facility. Clinical exclusion criteria vary based on illness and can vary depending on home hospital programs and countries within which care is conducted. In this research, clinical exclusionary criteria are not detailed explicitly, as this is not intended to be a medical study. In this research, clinical eligibility is determined as a rate or percentage of patients deemed medically eligible for a home hospital suitable illness, where otherwise inpatient care would be required. A range of low, most likely, and high eligibility rates is used as a part of a sensitivity analysis; using varying rates from past studies to develop the range allows the model to present results based on different programs, patient mixes, national healthcare standards, and physicians' medical judgments. Although only illnesses that have been verified to be suitable for home hospital in U.S. studies are used in this research, international studies are incorporated in developing ranges of clinical eligibility for each illness. This is on account of the limited number of American studies publishing clinical eligibility rates, and to develop a comprehensive range of rates to represent various home hospital scenarios.

In determining which past studies to include in using to develop a range of eligibility rates, we required various criteria. The reviewed studies needed to match our definition of home hospital care, in which active care was delivered by medical professionals in an individual's residence and which acted as a substitute for admission to an inpatient ward for short-term acute care. We only included studies that cared for patients aged 18 years or older. Past studies needed to operate under ED admit models, inpatient transfer models, and/or community referral models. We only considered illnesses to be suitable for home hospital in our study for those illnesses that have been examined in U.S. studies. However due to the small sample of studies in the U.S. with our required criteria and data, we included international studies for determining eligibility rates of these suitable illnesses. Publications presenting systematic reviews of home hospital studies were used to screen potential studies for our required criteria and to target studies with methodological quality and low risk of bias. Additional sources were identified by reviewing government issued documents or reports. A concern with our approach is publication bias. There could be studies that were never known to us if their publication was influenced by the results. The goal for this study is to develop a range of rates, rather than establishing a precise eligibility rate. Developing a sensitivity range of low, most likely, and high eligibility rates should help reduce the impact of perhaps missing unavailable studies that would have been available for our review. These past studies, which provided clinical eligibility rates, likely offered conservative percentages of patients who are eligible. This may have been due to issues such as clinical eligibility rates which incorporated various other criteria (clinical, social, and patient consent), limitations in hours of operation for accepting admissions to home hospital, limited capacity in home hospital programs, and chaotic atmospheres in EDs leading to missed evaluations for home hospital referrals (Cryer, Shannon et al. 2012). In all, 17 studies are included in developing a sensitivity range of eligibility rates. The 17 studies date back to when Leff, Burton et al.'s pioneering American work was beginning in 1996 up through

the two most recent publications in 2010. Of the 17 studies, one was based in the U.S., three in Australia, three in Scotland, two in Italy, two in England, two in New Zealand, two in Spain, and one study each in Canada and Sweden.

The range of eligibility rates are characterized as rates considered as most likely to be experienced, rates considered to be on the low eligibility end of the spectrum, and rates considered to be on the high end of the eligibility spectrum. On account of the limited clinical eligibility rates published in the U.S., expert analysis is used to develop the rate considered to be and termed the Most Likely. The Low eligibility rate is developed by a method of collecting the clinical eligibility rates from past literature that are lower than the Most Likely rate developed by expert analysis. From this group of rates, the median is taken as the Low rate for clinical eligibility. Similarly, the High eligibility rate is determined by taking the median of the rates from past literature that were above the Most Likely rate. This method for establishing clinical eligibility rates to conduct a sensitivity analysis is useful in that it provides various eligibility scenarios that could be experienced over a variety of hospitals, case mixes, and locales. Further, the manner in which the medians are used for Low and High rates prevents extreme values or outliers to be used. This is valuable considering eligibility rates are included from many different programs around the world. Similar to the use of a triangular distribution, this method for establishing the range of eligibility rates is useful considering the limited data and the most likely outcome relatively known from expert analysis.

Expert analysis to determine the Most Likely eligibility rate is established by Dr. Bruce Leff, professor of Medicine and Public Health at Johns Hopkins University and lead developer of the Hospital at Home program. Contemporary U.S. home hospital studies largely employ clinical exclusionary criteria closely modeled after validated criteria in Leff, Burton, et al.'s work (1997). Dr. Bruce Leff is a recognized leader of this pioneering study. Further, Dr. Leff either led or was a consulting partner in 5 of the 6 home hospital programs which have published studies taking place in the U.S. at the time

of this study. Leff has experience evaluating American home hospital programs in Maryland, New York, Massachusetts, Oregon, and New Mexico. He was also an advisor for the private home hospital corporation, Clinically Home, based in Tennessee. Beyond the U.S., Leff has collaborated with home hospital programs in Italy. Of published authors of home hospital studies in the U.S., Dr. Leff is the only contemporary researcher found in recent literature to hold experience evaluating home hospital in multiple hospital sites, cities, and types of home hospital programs. Based on Dr. Leff's experiences with home hospital programs across multiple sites and implementations, the following rates of clinical eligibility are likely to be experienced for each of the following conditions and are characterized in this study as the Most Likely rate: cellulitis = 30 percent; Chronic Obstructive Pulmonary Disease (COPD) = 25 percent; Community Acquired Pneumonia (CAP) = 20 percent; Congestive Heart Failure (CHF) = 25 percent; Deep Vein Thrombosis (DVT) = 50 percent (B. Leff, personal communication, October 6, 2013). As described previously, these clinical eligibility rates represent a rate or percentage of patients of the total patients who have a suitable home hospital illness that are medically eligible for home hospital care; the remaining patients with the suitable illness would be expected to be admitted as an inpatient to a hospital facility. A summary of eligibility rates is presented in Table 4.

The Low clinical eligibility rate is established as the median rate value of the eligibility rates found in approved published home hospital studies that are less than the Most Likely value. One cellulitis study reported a clinical eligibility rate lower than the Most Likely rate; so 25 percent is used as the Low eligibility rate for cellulitis treatment. Two COPD studies reported rates lower than the Most Likely rate, 10 percent and 14.9 percent, respectively. The median value used for the Low rate for COPD patients is 12.5 percent. Two CAP studies reported a clinical eligibility rate lower than the Most Likely rate, 10 percent and 17.7 percent respectively. The median rate used for the Low eligibility rate CAP patients is 13.9 percent. One CHF study reported a clinical eligibility

rate lower than the Most Likely rate; 18.7 percent is used as the Low eligibility rate. One DVT study reported a clinical eligibility rate lower than the Most Likely rate; 38.3 percent is used as the Low eligibility rate.

The High clinical eligibility rate is established as the median value of the eligibility rates found in approved published home hospital studies that are higher than the Most Likely value. Two cellulitis eligibility rates were reported higher than the Most Likely rate, 33 percent and 60 percent respectively. The median value used for the High rate for cellulitis patients is 46.5 percent. Nine COPD rates were reported higher than the Most Likely rate, ranging from 27.7 percent to 54.2 percent. The median value used for the High rate for COPD patients is 34.4 percent. Three CAP studies reported a clinical eligibility rate higher than the Most Likely rate, ranging from 30 percent to 46 percent. The median rate used for the High eligibility rate for CAP patients is 30 percent. Four CHF studies reported clinical eligibility rates higher than the Most Likely rate, ranging from 26.7 percent to 60 percent. The median value used for the High rate for CHF patients is 43.8 percent. One DVT study reported a clinical eligibility rate higher than the Most Likely rate; 58 percent is used as the High eligibility rate.

Table 4 Clinical eligibility rates for suitable home hospital illnesses

Illness	Low	Most Likely	High
Cellulitis	25.0%	30.0%	46.5%
COPD	12.5%	25.0%	34.4%
CAP	13.9%	20.0%	30.0%
CHF	18.7%	25.0%	43.8%
DVT	38.3%	50.0%	58.0%

Integrating the Hospital System with the ED

Discrete event simulation (DES) modeling was used as the method for analyzing and understanding the impact of remote hospital care on ED crowding in this study. DES models are commonly used tools in the hospital industry; ED facilities particularly are often modeled using DES to compare different scenarios, optimize performance criteria,

and to assess and optimize resource allocation plans (Law, Kelton et al. 1991). DES models a system as a network of queues and activities, allowing for individual entities within the system to be followed and tracked. Being able to track individual patients and staff make DES models a desired tool when individuals have differing characteristics from one another. The processes in DES are often described by probability distributions. DES handles variability well, which is useful in an industry like hospitals where there are so many variables that may change by the hour, day, or with randomness.

An analysis approach is established to apply home hospital's impact on the hospital system in the DES model. Since remote hospital care is expected to impact crowding by way of factors outside the ED, such as inpatient bed demand, output factors such as patient flow into and out of inpatient beds is assessed. This study develops a DES model encompassing bed demand and patient flow to assess home hospital's impact on the hospital system. The methods for addressing the integration of interventions within the hospital system and for developing the model are presented in this chapter.

Study Setting

This was a retrospective study that developed a discrete event simulation (DES) model on patient flow at an urban, academic, tertiary care hospital facility. The model will be referred to in this study as the "case model". Data, for the model, was collected in 2012. The model was built in Arena Simulation software, by Rockwell Automation Technologies, Inc. At the time for which the events occurred in the collected dataset, the inpatient hospital facility serviced 474 beds. The 474 beds were grouped into 30 floor units. Nine of the units accounted for 93 intensive care unit (ICU) beds; three units accounted for 56 cardiac telemetry beds. The remaining units and beds were made up of various specialties of medical and surgical beds. The case hospital is considered a specialty hospital, with high acuity patients. Patients are placed in beds in a deliberate manner, best matching the patient's care needs with the most applicable caregivers of a

particular floor unit. At the time for which the events occurred in the collected dataset, the case hospital's emergency department saw around 37,000 visits per year with the highest patient acuity in the country, an admission rate of about 24 percent, and serviced 25 beds for treatment.

Data

Hospital operations data were collected for a one-month period in 2012 from the case hospital that included demographic, clinical, operational, and time-stamped information. The study received IRB approval by the case hospital's IRB office and the IRB office at Georgia Institute of Technology. The analysis included only weekdays, as there was considerable variation between weekdays and weekend days with respect to hospital operations, including but not limited to elective and urgent admissions, hospital care staffing, and environmental/cleaning services staffing levels. Additionally, home hospital programs have typically only been in operation during the weekdays based on current programs in the U.S. and the programs that have been researched in the literature. Patients were included in the analysis if they were admitted to an inpatient bed from one of four primary admission sources: as an unscheduled admission from the ED, an urgent admission from the hospital lobby, a scheduled admission such as an elective procedure, or a transfer admission from another hospital. Data was collected from the case hospital's research warehouse database.

The initial data sample collected included 17,497 patients. Data was excluded for patients that did not occupy one of the 474 inpatient beds at the case hospital's main campus facility. These patients represented single-visit outpatients, patients discharged directly from the ED, mental health patients, rehabilitation patients, and patients admitted to the orthopedic and spine center. The mental health patients, rehabilitation patients, and orthopedic and spine patients were all treated in a separate care facility from the main campus facility and so did not account for bed demand on the 474 inpatient beds. The

final sample of patient data collected for analysis included 2,523 patients. Of these patients, 412 were already in a hospital inpatient bed at the start of the month and 2,110 patients arrived to the hospital sometime during the month. Of the 2,110 patients admitting to the hospital, approximately 37 percent admitted from the ED, 32 percent admitted as elective patients, 17 percent admitted as urgent patients, and 14 percent admitted as transfer patients. See Table 5 for patient data admission sources and admission rates for the month. The average midnight bed occupancy rate for the month studied was 89.2 percent, with an average weekday occupancy rate of 90.5 percent.

Table 5 Patient data admission sources and admission rates

Source	ED	Elective	Urgent	Transfer
Admit Rate	37%	32%	17%	14%

Additional patient data was collected for determining home hospital suitability in the model. Patients were evaluated against the clinical and social eligibility criteria presented in Chapter 3. This data is described as follows.

Clinical Data

This study evaluates home hospital for the five suitable illnesses discussed in Chapter 3: CAP, cellulitis, CHF, COPD, and DVT. While patients may present with other conditions as well, the primary diagnosis for admission and care should be one of these five suitable illnesses (Leff, Burton et al. 2005). Patient data was collected for the case hospital regarding clinical diagnoses and illness treated during patient hospital visits in the form of diagnostic related group (DRG) and International Classification of Diseases (ICD) 9 codes. DRG codes are a classification system to group types of patients in a manner that relates to the resources and costs incurred by the hospital (Averill, Goldfield et al. 2013). The codes are used by the Centers for Medicare and Medicaid for hospital payments of Medicare beneficiaries. DRG codes were established to contain

patients with similar patterns of resources required for care and who are similar from a clinical perspective. Therefore this study utilizes DRG codes as the main method for identifying patients with a suitable home hospital illness for all patients admitted to the hospital.

Social Criteria Data

Social eligibility criteria was evaluated for patients in the hospital system, and so corresponding data was collected. Patient age at time of admission was collected. Zip codes for each patient were collected to estimate the distance each individual lived from the hospital facility. As discussed earlier in this chapter, the average rate of uncompensated care costs (six percent) is used to estimate the percentage patients not living in a suitable residence for home hospital care.

Simulation Model Design

This study built a model representing a one-month period of hospital patient flow into and out of inpatient beds. The model is intended to accurately represent patient flow in the hospital and to accurately represent how long ED patients wait for requested hospital beds. The model runs from time zero hours to time 744 hours, which accounts for 31 days. The model records results for four full weeks between time zero and time 672. Discrete event simulation (DES) modeling was used as the method for analyzing and understanding the impact of remote hospital care on ED crowding in this study. DES models are commonly used tools in the hospital industry. DES models a system as a network of queues and activities, allowing for individual entities within the system to be followed and tracked. Being able to track individual patients and staff make DES models a desired tool when individuals have differing characteristics from one another. The variables in DES are described by probability distributions. DES handles variability well,

which is useful in an industry like hospitals where there are so many variables that may change by the hour, day, or with randomness.

The hospital system is modeled as a network of entities, which represent patients, requesting resources, which are beds. The patients act as customers, and the beds act as servers. This study evaluates the hospital system empirically. Arrival times for the applicable patients are scheduled based on the data collected. Once arriving to the system, each patient follows a sequence of bed requests and lengths of stay for each bed placement as documented in the data. Some patients arriving to the hospital were cared for in a single bed over the length of the visit and were discharged. While others were transferred between different beds and floor units, with some patients transferring up to seven times within the month that data was collected. The model takes into account specialized bed requests for particular floor units in the system. As the case hospital strives to match patients with applicable specialty caregivers in certain floor units, the system is modeled with the 30 unique floor units and beds are requested for a particular floor unit as reported in the data.

Regarding the patients whose admission source is the ED, the arrival time signifies when care of the patient is complete in the ED, the physician has decided the patient needs to be admitted to the hospital, and so a request for an inpatient bed has been made for the patient. At this time, a bed placement task occurs, representing the time it takes a bed placement staff member to receive and fulfill the request. Once the bed placement task is complete, a hospital bed is seized for the ED patient if available. If no bed is available, the patient must wait. When an available bed is seized and reserved for the ED patient, a nurse report task must be completed representing the tasks required before transporting the ED patient to the inpatient bed.

Arrivals and Length of Stay

As shown in Figure 10, each inpatient admission was classified by admission source as “ED” admission, “Urgent” admission, “Elective” admission, or “Transfer” admission. Patient schedules for arrival and bed placement were derived from timestamps in the dataset. The inpatient dataset included inpatient bed demand for elective, urgent, and transfer patients by way of timestamps representing reservations of beds for patients admitting to the hospital, reservations for bed movements to other beds within the hospital during the hospital visit, which will be referred to as internal transfers in this study, and discharges from the patient’s final bed during the visit to the hospital. For urgent, elective, and transfer admission sources, the timestamp of the patient’s 1st bed reservation was used to denote arrival into the system for initial bed demand and the utilization of a bed from the available bed resources. Timestamps representing movement out of a current bed and into another bed unit, or timestamps for discharges from the hospital, represented a bed being emptied, ready to be cleaned, and eventually made available for the stock of available bed resources for future bed demand. Once a patient requests and seizes a bed in the model, the patient’s length of stay in the bed is derived from the time between bed placement into the first bed and bed placement into a second bed. If a patient was discharged after care in a single bed, the length of stay in the bed is calculated by taking the difference between time of bed placement into the first bed and time of discharge. In the model, once a bed is seized and the time of length of stay is completed, the patient either requests the following bed unit in his/her sequence, or exits the system if the patient was discharged.

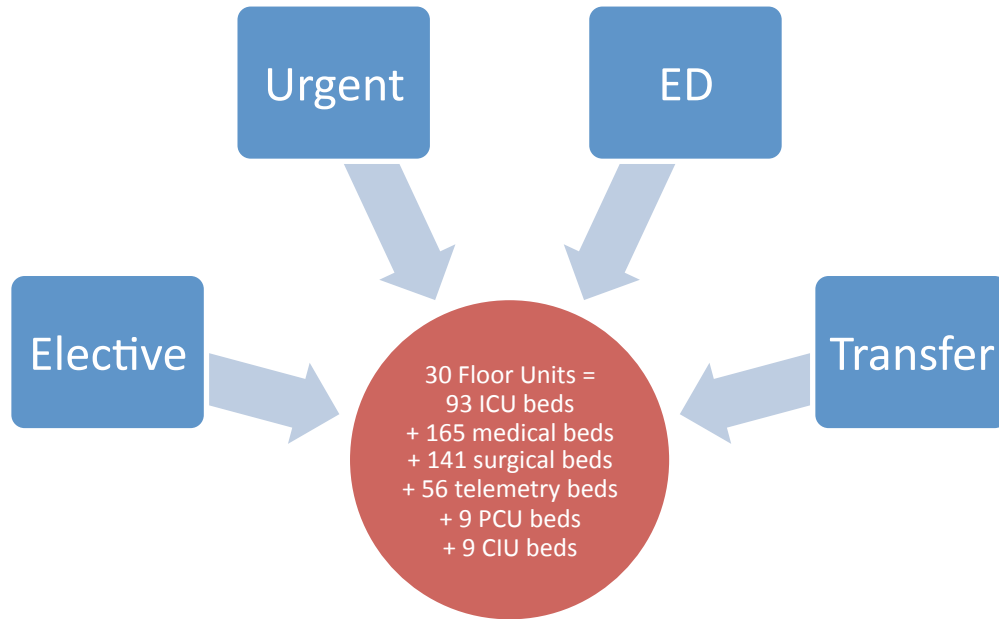


Figure 10 Admission source and server pool configuration

The ED patient dataset was made up by merging timestamps from events in the ED and timestamps of events occurring during the patient's hospital stay. The final analysis for the ED patient dataset included 2 chronological timestamps for each ED patient to represent arrival into the system: "bed request" and "ED departure" timestamps. The "bed request" timestamp represented arrival into the model, and indicated when care is completed in the ED and an inpatient bed was requested. Only ED patients that were admitted to the hospital were used in this study; patients discharged from the ED never requested inpatient beds and so never arrive in the system. The "ED departure" timestamp represented when the ED patient physically was transferred to an inpatient bed, and was used to calculate boarding time in the ED. After the ED patient was physically admitted to the inpatient facility, the ED patient dataset also included timestamps of events occurring during the patient's hospital stay equivalent to those of the elective, urgent, and transfer patients: timestamps for internal transfers and discharges from the patient's final bed during the visit to the hospital. Like the inpatient dataset, these timestamps were used to derive length of stay times in each bed.

The initial state of the model is based on patient data from the beginning of the first day of the studied month. The model begins with the 412 existing patients occupying beds in their respective floor units at time zero. This accounts for about an 87.5 percent inpatient occupancy rate. As the month is simulated, the existing patients occupy each scheduled bed placement for the given length of stay until exiting the system for discharge. Thirty of the initial existing patients are never discharged from the model, as their lengths of stay span the entire month.

Model Policies and Elements

This section describes how the simulation model operates once patient information populates the system, and as patient arrivals begin to request beds in the model. The ranking of how patients are assigned beds is discussed. Then we discuss the tasks that are required to be completed for responding to patient bed demand requests. The three main tasks modeled in this system are the Bed Placement Task, the Nurse Report Task, and the bed cleaning task. The Bed Placement Task represents various tasks and responsibilities of a hospital's bed management office to assign and reserve an inpatient bed for an ED admit patient. The Nurse Report Task represents the tasks and responsibilities required to transfer an ED patient to an inpatient bed once a bed is reserved. The bed cleaning task represents the time it takes to clean a previously occupied bed unit to be prepared for the next patient. Bed cleaning is modeled for all patient bed requests (i.e. from elective, urgent, transfer, and ED admit sources). However, the Bed Placement and Nurse Report Tasks are only modeled for ED admissions, as the wait times to secure a bed for elective, urgent, and transfer patients fall outside the scope of this study. Further, the timestamps used in our modeling for these patient types occur at a time after the bed placement responsibilities are completed. Tasks that would be equivalent to the Nurse Report Task for elective, urgent, and transfer patients are not incorporated in our model since the time it takes to move a patient to a

reserved bed does not impact ED boarding times. Once a bed is reserved, an ED patient cannot be assigned the bed, regardless of whether the elective, urgent, or transfer patient is physically occupying the bed yet. The tasks are employed to facilitate patient flow in the simulation model as illustrated in Figure 11, where the probabilistic tasks are hatched. The modeling of each task's probabilistic elements are presented and described in this section.

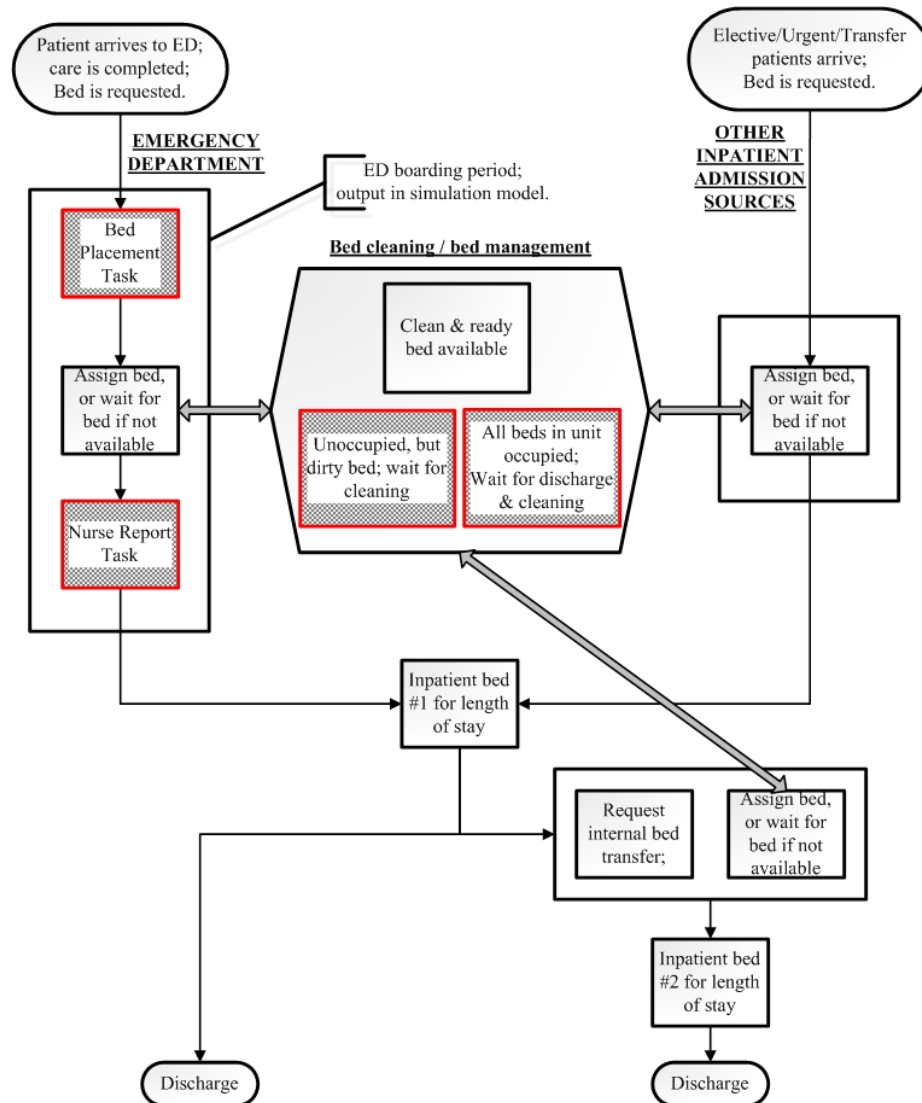


Figure 11 Operational tasks facilitating patient flow in model

Patient Priority Ranking

As patients seize and occupy bed resources, a queue forms if a bed is requested from a floor unit at full capacity. If more than one patient arrives during this time in which beds are unavailable, a priority policy typically exists to determine which eligible patient is assigned to the first freed bed. This patient priority rank can be established based on each hospital's own situation. The priority ranking used in this model is based on discussion with the case hospital's bed placement staff and is comparable with priorities given in the literature (Powell, Khare et al. 2012, Shi, Chou et al. 2012). In the model, elective admits and urgent admits are assigned the highest priority ranking for bed assignment. Second priority for bed placement goes to ED admits. Third priority goes to Transfer admits. This ranking is based on the ranking that the case hospital employs, and is similar to priority lists in past research (Powell, Khare et al. 2012, Shi, Chou et al. 2012, Hornfeck 2014). The high priority of elective patients is justifiable as they are typically scheduled admits and high revenue customers which a hospital would presumably like to keep on schedule. Urgent patients also deserve high priority as these patients present to the hospital through lobby admissions, where nurse care is not delivered. Transfer admissions are given last priority, as there often exists significant variability in when the patient will arrive to the facility. Further, they are presumably being treated and are not in urgent need of care. If multiple patients of the same admission or priority classification are waiting to seize a bed, the patient who has been waiting longest receives higher priority.

Bed Placement Task Delays

When an inpatient bed is requested for an ED patient, certain tasks are required to be completed in order to procure the bed assignment. The first step is to determine if the requested bed type or floor unit is available and ready for additional patient care. Our

model incorporates two scenarios in which a bed is not available: 1) if all staffed beds in the requested unit are occupied by patients at the time of request; 2) if beds in the unit that are not occupied are dirty or in the process of being cleaned. Regardless of whether there exists a bed shortage due to either of these scenarios or whether beds are available, certain tasks must be completed before bed assignment can take place. This section discusses how the model represents the time delay associated with this delay, referred to in this study as Bed Placement Task delays.

The Bed Placement Task delay represents the time it takes for the bed management staff to allocate a bed to the patient. This process is made up of various steps and responsibilities. Upon receiving a bed request, the bed management staff must review and assess the current bed demands so as to select a bed that best matches the medical needs of the patient. Before finalizing the bed assignment, the staff member must negotiate with the hospital ward to secure acceptance. If the ED patient's bed requirements have changed due to changes in medical condition, an alternate bed must be searched for and selected. Empirical observation of the ED data supports the need for incorporation of a bed assignment task delay, as there is always a span of time between when a bed is requested and when a bed is assigned in the dataset. Given bed availability was not an issue, discussion with the case hospital bed management office led to a typical maximum task-time of 30 minutes for bed placement negotiation and selection (Hornfeck 2014).

To develop a probabilistic estimation for the Bed Placement Task delay, an assumption is made based on discussions with case hospital staff that ED patient data with time delays of more than 30 minutes elapsing between bed request and bed assignment were due to bed shortage issues. The remaining times under 30 minutes were used to develop a probability distribution to represent the Bed Placement Task delay. The bed placement data accounted for 260 observations and Table 6 presents summary statistics on the data. The data was run through ExpertFit software (Averill M. Law and

Associates) to estimate a probability distribution that represents the data adequately. The program determines which distribution best represents the data, and the provided distribution is evaluated using goodness-of-fit tests assessing the null hypothesis that a population of data is an independent sample from a particular fitted distribution (Law, Kelton et al. 1991). If the test statistic is greater than the critical value, the null hypothesis (that the data is an independent sample from the fitted distribution) is rejected. Otherwise, the null hypothesis is not rejected. The bed placement data was run through ExpertFit, which evaluated 40 distributions through its distribution selection algorithm. ExpertFit assessed the Johnson SB probability distribution to be the best relative representation for the bed placement data. The following null and alternative hypothesis was tested for goodness-of-fit:

H_0 : data from the dataset is an independent sample from a Johnson SB distribution

H_1 : data from the dataset is not an independent sample from a Johnson SB distribution

ExpertFit concluded that the absolute evaluation for the Johnson SB distribution is “good”, which suggests there is no reason for concern regarding the fit. Additionally, the chi-square test gives a test statistic of 18.53846, which is less than the critical value of 23.685 at the 0.05 level. Therefore, we fail to reject the null hypothesis at the 0.05 level, and the chi-square test fails to reject the Johnson SB distribution as a good fit for the data at the 0.05 level. These results do not mean that the Johnson SB distribution is the exact distribution that produced the data, however there is no reason to believe that based on the test that the Johnson SB distribution does not provide a good model for the data. Figure 12 shows a scatter plot of the data signifying good independence, and Figure 13 presents the P-P plot of the Johnson SB distribution indicating an adequate fit presenting an approximately linear plot that is close to the line for the range of the sample. The model truncates the distribution at 0.5 hours to account for our assumption for the typical maximum task delay based.

Table 6 Summary statistics of Bed Placement Task delay data sample

Number of observations	260
Min	0.013 hours
Max	0.494 hours
Mean	0.198 hours
Median	0.174 hours

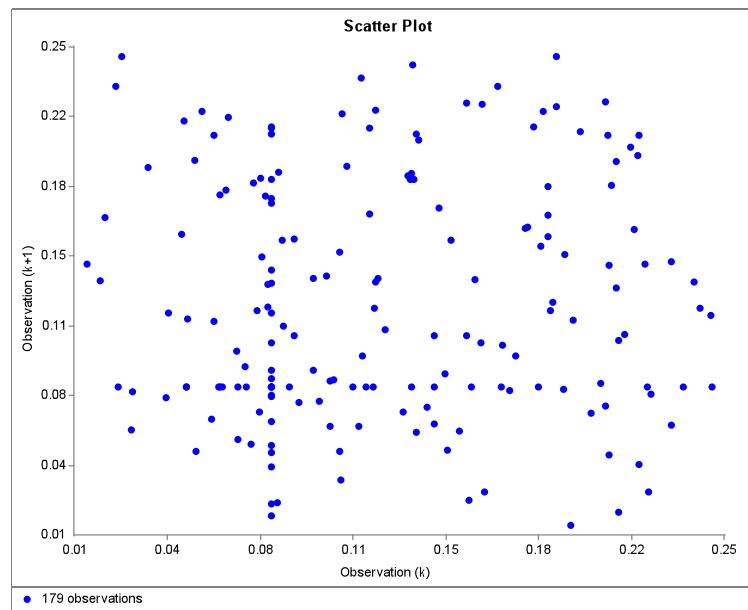


Figure 12 Scatter plot of Bed Placement Task delay data

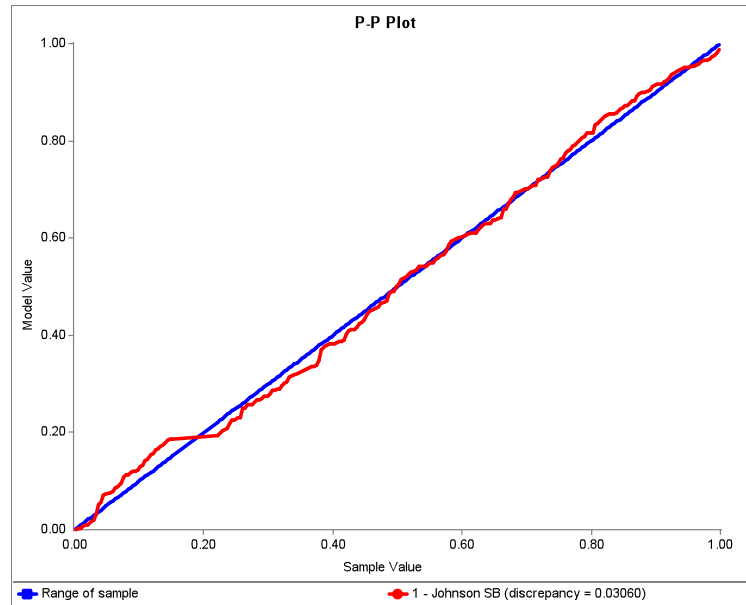


Figure 13 P-P plot of Johnson SB distribution for bed placement task delay

Bed placement task delays are incorporated in the model for ED patients admitting to their first bed during a hospital visit. The task delay is not incorporated for any other bed movements during a visit, nor is it used for elective, urgent or transfer patients in the model. The collected ED data included satisfactory timestamps for bed request and assignment times. However, request timestamps for patients requesting beds within the inpatient hospital facility were often missing. This accounts for initial bed placement of elective, urgent, and transfer patients, and for internal bed movements or transfers between beds during patient visits. Only about 20 percent of bed placements included bed request timestamps. Therefore the timestamps used for bed movements occurred at the bed reservation event time, which is after the bed placement task takes place.

Nurse Report Task Delay

After a bed request has been made on behalf of an ED patient and the bed placement task responsibilities have been carried out, an inpatient bed is assigned and reserved for the patient. At this point, a number of other tasks need to be completed before the ED patient discharges from the ED and is transferred to an inpatient bed (Jean

2014). These tasks are represented by the Nurse Report Task delay in the model. The two main tasks this delay takes into account are: 1) the ED nurse must write and submit an electronic report for the patient; 2) the ED nurse must complete a call report in which the nurse must successfully contact the ward nurse where the patient has been allocated a bed to communicate patient medical information, patient history, physician care information, etc. Other steps that must also be completed include ensuring that all test results are complete, checking the patient's vital signs to ensure the patient is stable and able to be transferred, and arranging a staff member to transport or escort the patient to the inpatient bed.

Delays can occur at various steps or tasks during this process. During the time at which the collected dataset occurred, the case hospital specifically had delay issues with the call report responsibilities (Jean 2014). At the time, ED nurses had difficulties connecting with inpatient ward nurses, and vice versa when ward nurses tried returning calls to ED nurses, as nurses can be busy attending to other patients. Other delays may have been attributed to arranging a staff member to escort a patient to the inpatient bed. ED support staff, or lab technicians, bear much of the responsibilities for transporting patients to their inpatient beds at the case hospital. These staff members were generally responsible for escorting patients in eight-bed zones. However other responsibilities include running equipment for labs, such as electrocardiogram (EKG) and radiography equipment, and at busy times they will also help with basic care for patients, such as starting intravenous (IV) fluids. ED nurses often were responsible for accompanying transports if the patient was heading to an ICU bed.

To develop a probabilistic estimation for the Nurse Report Task delay, ED patient timestamp data was employed to test and generate a probability distribution. The distribution was based on the time elapse between the point at which an inpatient bed was assigned to an ED patient and when the patient departed the ED. The data was run through ExpertFit software (Averill M. Law and Associates) to estimate a probability

distribution that represents the data adequately. The program determined that the log-logistic distribution best represented the data sample. See Table 7 for summary statistics of the data sample. The following null and alternative hypothesis was tested for goodness-of-fit:

H_0 : data from the dataset is an independent sample from a log-logistic distribution

H_1 : data from the dataset is not an independent sample from a log-logistic distribution

ExpertFit concluded that the absolute evaluation for the log-logistic distribution is “good”, which suggests there is no reason for concern regarding the fit. For a log-logistic distribution evaluation, ExpertFit provides three goodness-of-fit tests: the Anderson-Darling test, the Kolmogorov-Smirnov test, and the chi-square test. In all three tests, the null hypotheses fail to be rejected at the 0.05 level. The test statistics and critical values for each test are presented in Table 8. These results do not mean that the log-logistic distribution is the exact distribution that produced the data. However there is no reason to believe, that based on the tests, the distribution does not provide a good model for the data. Figure 14 shows a scatter plot of the data signifying good independence; Figure 15 presents the P-P plot of the log-logistic distribution indicating an adequate fit presenting an approximately linear plot that is close to the line for the range of the sample. The simulation model truncates the given log-logistic distribution at 8.5 hours to account for our maximum task delay based on the data sample. This truncation was incorporated in order to limit any skew to larger values for samples drawn from the distribution in the model.

Table 7 Summary statistics of Nurse Report Task delay data sample

Number of observations	776
Min	0.07 hours
Max	8.49 hours
Mean	1.57 hours
Median	1.33 hours

Table 8 Goodness-of-fit test results on Nurse Report Task delay data sample

Goodness-of-Fit Test	Test Statistic	Critical Value
Anderson Darling	0.561	0.660
Kolmogorov-Smirnov	0.690	0.780
Chi-square	32.041	54.572

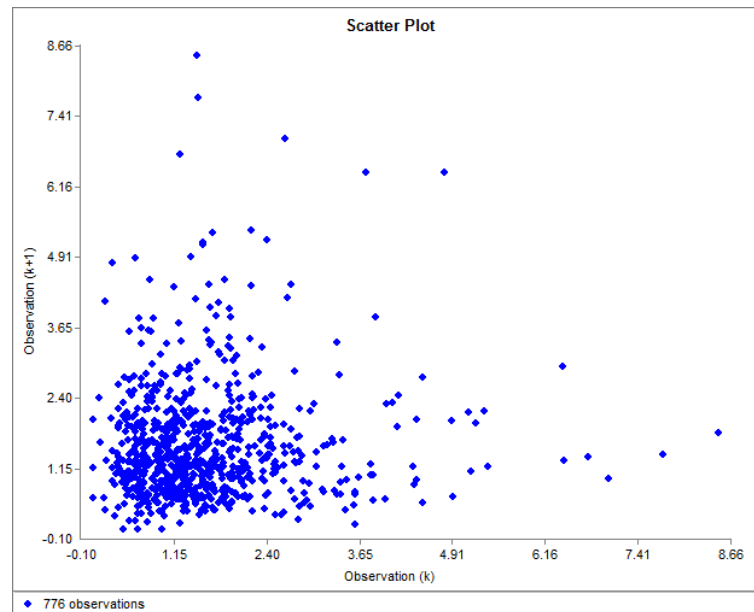


Figure 14 Scatter plot of Nurse Report Task delay data

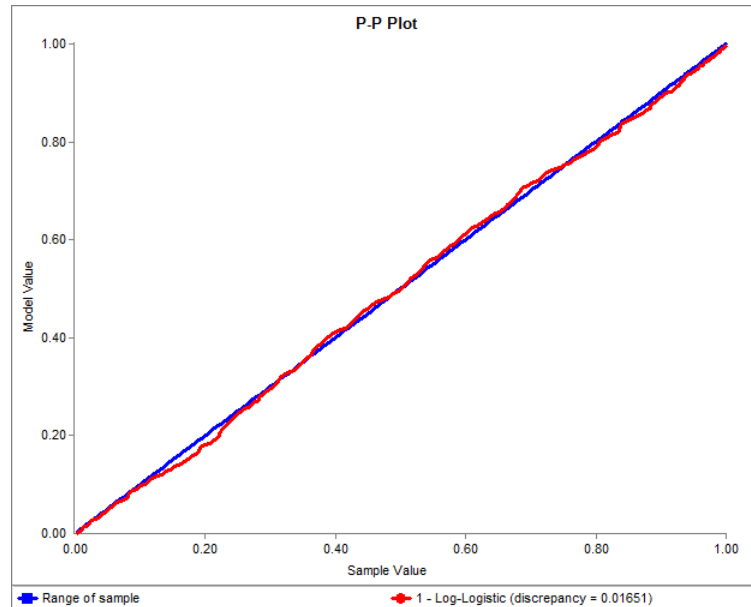


Figure 15 P-P plot of log-logistic distribution for Nurse Report Task delay data

Bed Cleans

In order for a bed assignment to take place at the case hospital, a clean and ready bed must be available in the requested floor unit (Hornfeck 2014). Our model incorporates this principle, as a bed cannot be seized or allocated to a patient until the bed resource has been delayed a certain time representing the time it takes to clean the bed and room. The department responsible for bed cleaning at the case hospital is the Environmental Services department, under the Facility Services branch of the organization. A bed cleaning staff member is expected to clean typical floor beds at a 30 minute rate, and isolation beds are expected to take about 45 minutes (Jackson 2014). Staffing levels can be highly variable day-to-day, and even hour-to-hour in a given day, for bed cleaning services. Day-to-day, staff can vary due to employees missing work or simply the transient nature of people in the industry (Jackson 2014). Staffing levels vary by the hour based on expected volumes of beds to be cleaned. However, due to the uncertain nature of knowing when patients will discharge from beds, staffing levels can be fluid even during a particular shift. During the afternoon shift when the volume of discharges generally peak, the case hospital tries to staff about 8 or 9 people solely

focused on bed cleaning. However depending on discharge timing and high bed demand, up to an additional five Environmental Services staff members may be pulled from cleaning ancillary areas to help with bed cleans. During non-peak times of the day, Environmental Services staff are not designated solely for bed cleaning. They are cleaning ancillary areas, such as special care areas, common spaces, offices, etc., in addition to mixing in bed cleans. During both peak and non-peak discharge times, bed cleans can be requested by the bed management office and thus prioritized to be cleaned before other beds. This particularly may occur if a surge of bed requests and discharges occur in a short timeframe, and bed management is seeking a quick turnaround time on getting the beds cleaned (Hornfeck 2014).

To incorporate bed cleaning into our model, we evaluated and included bed cleaning turnaround times, as opposed to modeling the highly variable staffing levels. This turnaround time measurement represents the time between when a patient leaves a bed and when the bed is reported as clean and ready for the next patient. Bed clean turnaround time data was collected from the Environmental Services group at the case hospital. Average turnaround times were reported for each floor unit on a daily basis throughout the month. Explained another way, for a given floor unit that encompasses a group of beds, the average length of time it took to turn dirty beds to clean beds was given each day. The number of cleans in the floor unit was also collected each day. The data collected does not account for the variability of turnaround times from one bed to another. The average times given for floor units represented various numbers of bed cleans each day, ranging from 1 to 14 cleans in a given unit per day.

Due to the lack of detailed data regarding bed cleaning, the bed clean turnaround times are assumed to have a triangular distribution. The triangular distribution is a bounded, continuous distribution commonly used in simulation models when the exact form of the distribution is not known, but estimates for the minimum, most likely, and maximum values are available (Kelton, Sadowski et al. 2002). To determine the initial

minimum, most likely, and maximum parameters, the collected data was used to develop a histogram. Before generating the histogram, extreme values were observed in the data. The initial dataset had a maximum turnaround time value of 9,777 hours, or about 407 days, an obvious red flag. Discussions with the Director of Operations for Environmental Services at the case hospital led to removing certain data from the dataset on the account of errors in the database program or special cases atypical from everyday operations (Jackson 2014). Average turnaround times greater than 61 hours were removed from the data. These times accounted for 9.8 percent of the collected turnaround averages. Although bias is a possibility in the expert analysis given by the case hospital Operations Director, it is believed that such long turnaround times are agreeably inaccurate or very uncommon for such a busy and high-occupancy hospital organization. After removal of extreme values, the minimum average bed clean turnaround time in the dataset was 0.23 hours; however 0.5 hours was used as the minimum parameter in the triangular distribution based on organizational goals put forth by the Environmental Services department. The maximum average bed clean turnaround time reported in the data was 9.35 hours, and was used as the maximum parameter in the Triangular distribution. A histogram of the dataset showed the bin ranging between 1.25 to 1.75 hours as the most common average bed cleaning turnaround time. The Director of Operations of Environmental Services at the case hospital supported 1.5 hours as the most likely turnaround time in a given day. The bed clean turnaround time dataset was investigated for differences between different days of the week. However, no significant differences were observed, as all days exhibited most likely time values in the 1.25 to 1.75 hour bin. Therefore, the Bed Turnaround Time delay used in the model is a triangular distribution with a minimum value of 0.5 hours, most likely value of 1.5 hours, and maximum value of 9.5 hours.

Boarding Hours

The case hospital boarding hours from the dataset are calculated as the time between when an inpatient bed is requested up to the point of departure from the ED. Boarding hours are recorded as an output or result in our hospital simulation model for ED patients admitting to inpatient beds. Similar to boarding calculated from the data, the model records boarding hours as the time it takes from an ED patient's arrival into the system up to the time when the patient begins to delay in an inpatient bed. This ED boarding timeframe is made up of the following steps:

- 1) Arrival into the system represents an inpatient bed request from the ED and initiates the start of ED boarding.
- 2) Bed Placement Task delay is initiated and completed.
- 3) An inpatient bed from the requested floor unit is seized. If a bed is not available, the patient waits in a queue until a bed becomes available and until the bed cleaning task is completed.
- 4) Nurse Report Task delay is initiated and completed.

The completion of these steps indicates the patient has departed the ED, and is ready to begin care in an inpatient bed for the duration of the length of stay.

Simulation Model Assumptions

Our hospital simulation model is used to examine the interface between the ED and the inpatient hospital facility. The model is developed with certain rules and assumptions that are discussed in this section.

The dataset used to build our simulation model was from a one month period in 2012. We assume the dataset represents a typical month that the case hospital might experience at other times of the year. This assumption is supported on account of validated population statistics. The dataset's average weekday hospital occupancy level

of 90.5 percent corresponds well with the average historical occupancy of about 92 percent (Hornfeck 2014). The ED admission rate of slightly under 30 percent for the month was similar to published rates for the case hospital ranging between 24 to 28 percent. Further, ED staff and researchers at the case hospital had developed a trusted model of the ED system based largely on the same month of data.

Regarding model operation, we assume the model starts at an inpatient bed occupancy equivalent to the beginning of the month of data collected, about 87.5 percent. As the model simulates hospital operation, we assume any and all inpatient beds are made available by inpatient discharges or internal patient transfers out of the bed to a different bed or floor unit. Further, it is assumed that the capacity of staffed beds is 474 beds and does not vary due to fluctuating staffing levels. It is assumed that during weekdays, staffing levels are not erratic enough to alter the capacity of staffed beds.

As two main components of patient flow are information and physical flow, this model makes assumptions as to how to incorporate these impacts (Zhao and Lie 2008). Regarding information flow, we model the system to begin functioning after information flow tasks such as patient sign-ins and registration. We assume that information flow, such as bed and medical equipment availability and communication problems between ED nurses and inpatient nurses, are incorporated through the Bed Placement Task and Nurse Report Task delays. Regarding the physical flow of patients, this study and model is particularly interested in the availability and demand of bed reservations. We are not focused on the patient's physical presence in a room, as the bed reservation of a room is what limits bed availability before physically occupying a room. Regarding the physical flow of ED staff to escort patients to beds and the seizure of transport equipment such as stretchers or wheelchairs, we assume the Nurse Report Task delay incorporates these potential causes for delay. We assume no causes for delay in ED staff, such as doctor and nurse availability for care, as the system begins modeling at the time which care is considered complete for the ED patient.

Simulation Model Verification and Validation

Model Verification

The model was run in Rockwell Automation Technologies' Arena simulation software, version 14.70. The aim of model verification is to develop a model that passes various verification tests, and ensures a high degree of certainty that the model is programmed and is operating correctly (Macal 2005). Therefore we verify our model through various tests. To ensure that the model is implemented and programmed correctly, the model specifications were discussed and supported by the case hospital's bed management department. To ensure that the model programming is free of errors or bugs, the "Check Model" feature was used in the software package, and resulted in no errors or warnings. To check if the model is operating correctly, we exercised the model for various extreme cases to ensure the system is reacting logically to these changes. We ran the system for 30 separate replications for the month-long period to test the various cases. Each 30 replication run tested how the model behaved with respect to changes in the initial occupancy level and changes to the bed cleaning turnaround time distribution. We tested for low and high initial occupancy levels, and for shorter and longer bed cleaning turnaround times. The results are presented in Table 9 and Table 10. The results indicate that the model reacts as expected to the changes, and that we can be confident that the model is operating acceptably.

Table 9 Model verification for extreme cases in initial occupancy level

	Initial Occupancy Level	Avg. Boarding Hours/day
Low	382	
Given	412	98.68 hours/day
High	442	

Table 10 Model verification for extreme cases in bed turnaround time delays

	Bed Turnaround Time	Avg. Boarding Hours/day
Low	Min: 0.5 hours Most Likely: 1.5 hours Max: 3 hours	65.82 hours/day
Given	Min: 0.5 hours Most Likely: 1.5 hours Max: 9.5 hours	98.68 hours/day
High	Min: 0.5 hours Most Likely: 1.5 hours Max: 18 hours	150.91 hours/day

Model Validation

After verification of the model, the model is tested for validity. Validation involves confirming that the model accurately behaves like the actual hospital system under study. The ultimate goal is to determine if the model provides accurate information about the system and that it is useful in addressing the investigation at hand (Macal 2005). An acceptable method for validation of a simulation model is to compare output values to the actual values seen in the system (Jurishica 2005). Therefore we ran the simulation model for 30 replications, and the output result for average weekday occupancy level was 90.2 percent. Comparably, the actual average weekday occupancy level at the hospital system over the period for which data was collected was 90.5 percent. We also tested our model for validation of the key output being studied in this investigation, ED boarding hour results. The results for the model's 30 replication run were analyzed to compare the ED boarding hour results against the actual boarding hours experienced in the system. Our study is interested in evaluating the boarding hours that an ED system experiences on a weekly basis. But because ED boarding hours can fluctuate from day to day according to varying rates of ED admissions, inpatient bed demand, and lengths of stay of existing patients, we test the boarding hours recorded for each weekday in the model against the actual hours experienced in the corresponding day

from the dataset. This level of daily analysis gives us confidence that the model is representing the distribution of boarding hours accurately throughout the seasonality of a week.

For each weekday during the month of evaluation, a one-sample t-test is conducted to assess whether the difference between the mean of ED boarding hours recorded in the model and the ED boarding hours recorded in the dataset is statistically different. The following null and alternative hypothesis was tested for each day's one-sample t-test:

$$H_0: \mu_{model} = \mu_{actual}$$

$$H_1: \mu_{model} \neq \mu_{actual}$$

If the resulting p-value is less than the given significance level, one can conclude that the model mean is significantly different from the actual boarding value at the given level of significance. After performing t-tests on each weekday of the simulated month, twelve days were unable to conclude that the model mean differed from the actual boarding value at the 0.05 significance level. The remaining eight days were concluded to have mean boarding values different from the actual boarding values at a significance level of 0.05. These eight days were investigated. Five days of the eight days had means greater than, but within 10 percent of, the target value from the dataset. The remaining 3 days had means greater than, but within 15 percent and within 10 hours of, the target values. Although these differences are statistically significant, it is believed that the differences do not prevent practical use of the model. This is especially valid given that the boarding differences, which ranged between 3.8 and ten hours, can be caused by one or two special cases in an actual day in the system. Nonetheless, these days were investigated, and questionable boarding times were explored.

As mentioned previously, there are times at the case hospital when bed cleans are prioritized to be cleaned before other beds. This particularly may occur if a surge of bed requests and discharges occur in a short timeframe, and bed management is seeking a

quick turnaround time on getting the beds cleaned. Further if multiple patients leave beds in a single floor unit in a short timeframe, bed cleaning staff may clean the beds one after another. This would give results for bed clean turnaround times on the lower end of the distribution. The challenge in modeling these scenarios lies in the human decision making element on the system. Priority bed cleans are often requested by a bed placement staff member requesting that a bed or group of beds in a particular floor unit be cleaned before other dirty units. While our system incorporates the range of bed clean turnaround times from 0.5 hours to 9.5 hours, inevitably some of the shorter turnaround times will be randomly assigned to floor unit beds where bed demand may not be high at the time. Therefore resulting in a clean and ready, but vacant bed. To more accurately represent the patient flow at times in the system, prioritized bed cleans are assumed to have occurred for certain beds. For these special instances, our model incorporates a Prioritized Bed Cleaning Turnaround time delay. The time delay distribution for the prioritized clean is a triangular distribution with a minimum value of 0.5 hours, most likely value of 1.5 hours, and maximum value of 1.5 hours, and is based on discussions with the Bed Management and Environmental Services departments at the case hospital (Hornfeck 2014, Jackson 2014). If a priority bed clean is requested, often either a bed cleaning staff member will direct efforts to clean the requested bed, or an ancillary environmental services member will be pulled to clean the bed.

In the eight days for which t-tests concluded that the model mean was different than the actual value, we observed particularly busy patient flow scenarios in the dataset that resulted in low ED boarding times, but higher boarding time averages in the model results. The scenarios included ICU bed requests from fully-occupied floor units and multiple bed requests from a single unit with batched discharges in the same time period. See Table 20 in Appendix A for the nine circumstances for which we assume priority bed cleans occur. These nine circumstances impact 36 bed cleans, which account for less than one percent of bed cleans in the model.

The other questionable boarding times investigated had to do with patients in the ED boarding for excessively long times, specifically when beds were seemingly available based on the empirical data. There were cases where a bed was requested for an ED patient, a long boarding time would ensue, and eventually the patient was admitted to a bed unit which in multiple cases had more than one bed available long before the patient finally departed the ED. Therefore, we assume the patient boarded in these excessive cases due to reasons not affiliated with typical patient flow and bed assignments. Instead, it is assumed that these patients boarded excessively due to one of the following reasons: 1) the patient is awaiting labs in the ED; 2) the physician knows that hospital admission will be required and so prematurely requests a bed before care is complete in the ED; 3) the patient's health deteriorates and care must continue in the ED. Seven patients are assumed to experience this ED departure delay, and have boarding times ranging between eight to 23 hours, all while beds are seemingly available for these patients. To simulate this assumed scenario, an ED Delay time is assigned to each of the seven patients before departure from the ED in the simulation model. See Table 21 in Appendix A for the seven patients for which the ED Delay assumption is made.

The model is re-run for 30 replications with the 9 cases of priority bed cleans incorporated. For each weekday during the month of evaluation, a one-sample t-test is again conducted to assess whether the difference between the mean of ED boarding hours recorded in the model and the ED boarding hours recorded in the dataset is statistically different. The t-test assumes that the population is normally distributed and that the data is random. Although the t-test should perform rather accurately for our sample size of 30, we verify that our data is from a normally distributed population with Anderson-Darling normality tests. The hypotheses for each day's test are:

H₀: data are from a normally distributed population

H₁: data are not from a normally distributed population

The results of the tests are displayed in Table 22 of Appendix A. As illustrated in the table, there is insufficient evidence to suggest that the data is not from a normally distributed population at the 0.05 level. The randomness assumption is met as each of the 30 points in each sample comes from an individual and separate replication from the next.

Since the normality and randomness assumptions are met, we perform the t-test on each weekday. The following null and alternative hypotheses were tested for each day's one-sample t-test:

$$H_0: \mu_{model} = \mu_{actual}$$

$$H_1: \mu_{model} \neq \mu_{actual}$$

Again, if the resulting p-value is less than the given significance level, one can conclude that the model mean is significantly different from the actual boarding value at the given level of significance. Table 11 displays the results of the t-tests performed for each weekday. As illustrated in the table, we fail to reject the null hypothesis at the 0.05 level for all days. Therefore, the data do not provide sufficient evidence to conclude that the model's mean daily boarding results are significantly different from the actual daily boarding hours for the corresponding days. These results do not mean that the simulation model is always equally accurate with reality on a given day. However it does lead us to believe that the model is a satisfactory gauge of the real-world hospital to be used to draw inferences regarding ED boarding hours experienced in the real system.

Table 11 T-test results of model mean against actual daily boarding hours

Day	Actual Boarding (hrs)	Mean Boarding (hrs)	p-value
1	82.61	82.44	1.000
2	102.53	99.40	0.080
3	82.68	83.73	0.533
4	56.58	56.01	0.615
5	129.33	127.43	0.219
6	75.74	77.71	0.108
7	146.71	149.46	0.318
8	72.06	70.74	0.394
9	76.24	78.81	0.195
10	104.45	104.97	0.736
11	195.17	200.09	0.080
12	161.06	163.44	0.196
13	55.76	58.29	0.111
14	83.18	83.09	0.959
15	72.00	74.61	0.157
16	71.79	71.82	0.981
17	100.36	98.52	0.253
18	73.97	72.17	0.222
19	80.13	77.97	0.093
20	89.43	87.42	0.160

Home Hospital Intervention Study Design

To identify and understand the relationship between home hospital and ED crowding, this study analyzes a DES model representing patient flow in the case hospital. The simulation model is used to compare the effects of various scenarios of home hospital implementation on ED boarding hours. One of the major causes for ED boarding is inefficient or imbalanced patient admissions resulting in a lack of inpatient beds (Viccielio 2008). So the focus of home hospital's impact on ED boarding is on the effects to inpatient bed capacity and timing of availability of beds.

Base Case Model

We begin by running and establishing a base case model of the existing hospital system, for which a home hospital program is not incorporated. We record the base case boarding rates for each week during the month for which the model runs. A weekly tally is recorded based on the expectation that a hospital organization would be interested in changes in weekly boarding rates over single days to assess how their ED system operates and performs generally. Monthly or seasonal variations may exist to a certain extent, but boarding is a chronic day-to-day and week-to-week issue that occurs year-round (Vicciello 2008). Further, a weekly sum of boarding hours is recorded since changes to patient admissions are expected to make impacts to bed availability and demand over multiple days due to typical patient lengths of stay extending over multiple days.

Home Hospital Intervention

Once the base case boarding rates are recorded for each week in the model, home hospital is incorporated into the system. We identify patients who present to the hospital with a suitable home hospital eligible illness, as listed previously in Table 2. Based on the eligibility rates presented in Table 4, we use these rates to randomly assign patients with a suitable illness to be clinically eligible for home hospital. The eligibility rates presented allow for a sensitivity analysis to be conducted regarding clinical eligibility for home hospital. Of the patients deemed clinically eligible, the social criteria that must be met to be admitted to home hospital is evaluated based on criteria presented in Table 3. Patients are evaluated for meeting age requirements, living within the catchment area, and will randomly be assigned to live in a fixed and adequate residence for home hospital. The patients that meet both clinical and social criteria are assigned to be admitted to home hospital. This process for assigning home hospital patients is repeated for each model replication. After running the model for the multiple replications, the ED

boarding results are compared with the base case boarding results. This analysis is repeated for all four weeks in the model to determine the impact that home hospital has on ED boarding hours.

Each home hospital referral model (ED referral, inpatient-transfer referral, and community referral) will be simulated for three scenarios while incorporating home hospital. The three scenarios offer options for how a hospital organization can utilize the home hospital impact on patient flow. Scenario One assumes any saved bed hours for inpatient beds will be used to care for ensuing patients demanding beds. This scenario acts as an effort towards an organization's goal to improve ED boarding times. Scenario Two assumes any saved bed hours through the home hospital program are reassigned to new, additional patients that are not in the simulated system. This scenario calculates the bed hours saved that can be reallocated at the discretion of hospital leaders. This scenario represents the result of hospital leadership with the goal to generate maximum revenue from the hospital facility. Scenario Three is a hybrid approach between Scenario One and Two. Half of saved bed hours will be utilized to improve patient flow and bed waiting times, and the other half will be saved for new, additional patients. The three scenarios for each referral model are titled and listed below.

This study and model assumes that home hospital staffing and equipment is adequate during operational hours. We assume no staff or equipment shortages to initiate care exist during operational hours. The models employ home hospital operational hours on weekdays between 8:00 am and 6:00 pm. Operational hours represents the times for which patients can be admitted to the home hospital program, either from the hospital facility or from a community site.

ED Referral Model Scenarios

An ED Referral Model will be run for various hospital scenarios. The ED Referral Model for home hospital is described in the "Characterization of Home

Hospital” section of Chapter Three as the source of admission to home hospital occurring in and during the patient’s ED visit. Admission to home hospital from the ED healthcare facility means that an individual never occupies an otherwise required inpatient bed. In the simulation model, the patient is evaluated and must meet the clinical and social home hospital criteria described in the previous section. In addition to the clinical and social criteria presented earlier, two additional criteria are instituted in order to more accurately identify potential home hospital patients: 1) a patient who requires an ICU bed is deemed unsuitable for home hospital care; 2) a patient’s overall length of stay should be five days or less (Leff 2014). Additionally, the ED patient must request admission to home hospital during home hospital operating hours in the simulation model. If these criteria are met, the model evaluates the patient for consent to home hospital. If the patient meets all of these criteria, the simulation model delays the patient in order to complete the Home Hospital Referral Task. This task delay represents the time it takes to process a home hospital admission, assign health care staffing, order equipment, and organize transportation. Detailed data regarding the time it takes to complete these tasks was not available at the time of this study. Discussions were conducted with existing home hospital program leaders at Presbyterian Healthcare Services and the Portland Veterans Affairs Hospital to estimate delay times. Often, tasks such as staffing availability checks and clinical and social eligibility assessments are conducted during ED patient care, and are completed before care is complete (Jenkins 2014, Thompson 2014). However, delays can occur if the home hospital referral is not initiated until late in the patient’s ED care, or if a home hospital physician believes an additional evaluation is necessary to determine if the patient is clinically eligible for home care. In our simulation model, we conservatively apply the following triangular distribution for the Home Hospital Referral Task delay: minimum = 0 hours; most likely = 1 hour; maximum = 2 hours. The three scenarios to be simulated for the ED Referral Model are named and described as follows:

Scenario 1 (ED): For ED patient that is admitted to home hospital, the freed inpatient bed is available for the next ED, elective, urgent, or transfer patient requesting a bed in the floor unit.

Scenario 2 (ED): For ED patient that is admitted to home hospital, the freed inpatient bed hours saved are reserved for use as hospital leaders see fit with respect to hospital organizational goals. For example, these bed hours could be used for high revenue elective patients.

Scenario 3 (ED): Hybrid of scenarios 1 and 2. For ED patient that is admitted to home hospital, half of the freed inpatient bed hours saved are available for the next patient requesting a bed and half are reserved for use as hospital leaders see fit.

Inpatient-Transfer Referral Model Scenarios

An Inpatient-Transfer Referral Model will be run for various hospital scenarios. The Inpatient-Transfer Referral Model for home hospital is described in the “Characterization of Home Hospital” section of Chapter Three as the source of admission to home hospital occurring in and during the patient’s inpatient hospital visit. Admission to home hospital from an inpatient bed leads to an individual’s inpatient length of stay occupying a hospital bed to be cut short. The inpatient is admitted to home hospital in the simulation model during home hospital operating hours in a couple of scenarios: 1) a minimum of 24 hours after initial length of stay in an inpatient non-ICU bed; 2) a minimum of 24 hours after internal transfer from ICU bed to non-ICU bed. When home hospital admission by way inpatient-transfer is not available due to requests outside the hours of operation, patients are transferred to home hospital once time of day is within the hours of operation again. Since patients initially spend at least 24 hours in the hospital facility for care, patients with total length of stays less than 30 hours are not

transferred to home hospital, and continue to occupy a hospital bed to complete the length of stay and discharge. This restriction is placed to realistically utilize hospital facility and home hospital program staff and resources efficiently. If a patient is considered near discharge, there would be little reason to initiate home hospital admission for the final hours of care. The scenarios to be simulated for the Inpatient-Transfer (IP-T) Referral Model are named and described as follows:

Scenario 1 (IP-T): For an inpatient that is admitted to home hospital, the freed inpatient bed is available for the next ED, elective, urgent, or transfer patient requesting a bed in the floor unit.

Scenario 2 (IP-T): For an inpatient that is admitted to home hospital, the freed inpatient bed hours saved are reserved for use as hospital leaders see fit with respect to hospital organizational goals. For example, these bed hours could be used for high revenue elective patients.

Scenario 3 (IP-T): Hybrid of scenarios 1 and 2. For an inpatient that is admitted to home hospital, half of the freed inpatient bed hours saved are available for the next patient requesting a bed and half are reserved for use as hospital leaders see fit.

Community Referral Model Scenarios

A Community Referral Model will be run for various hospital scenarios. The Community Referral Model for home hospital is described in the “Characterization of Home Hospital” section of Chapter Three as the source of admission to home hospital occurring during an individual’s visit to a physician’s office or clinic. Admission to home hospital from a physician’s office or clinic results in the patient never presenting to the hospital to occupy an otherwise required inpatient bed. The individual is admitted to home hospital from the community in the simulation model if the patient does not request

an ICU bed, if the patient meets the clinical and social eligibility criteria, and if arrival to the system occurs during home hospital operating hours. The scenarios to be simulated for the Community (COMM) Referral Model are named and described as follows:

Scenario 1 (COMM): For an inpatient that is admitted to home hospital, the freed inpatient bed is available for the next ED, elective, urgent, or transfer patient requesting a bed in the floor unit.

Scenario 2 (COMM): For an inpatient that is admitted to home hospital, the freed inpatient bed hours saved are reserved for use as hospital leaders see fit with respect to hospital organizational goals. For example, these bed hours could be used for high revenue elective patients.

Scenario 3 (COMM): Hybrid of scenarios 1 and 2. For an inpatient that is admitted to home hospital, half of the freed inpatient bed hours saved are available for the next patient requesting a bed and half are reserved for use as hospital leaders see fit.

Fully Integrated Home Hospital Program

A final model runs the simulation incorporating a fully integrated home hospital program. This simulated hospital system includes the ED Referral, Inpatient-Transfer, and Community Referral models together to assess the impact on ED boarding. The three scenarios that are run for each individual referral model are evaluated for the fully integrated simulation.

CHAPTER 5

ANALYSIS OF VARIOUS HOME HOSPITAL SCENARIOS

This chapter presents the results of the analysis of the various home hospital scenarios tested with our simulation model. We seek to understand the relationship of the interface between the ED and the inpatient hospital facility. The patient data collected was evaluated to determine patients who meet the various criteria to be suitable and eligible for home hospital. Various simulation models were run to assess any impact on ED boarding performance of the case hospital system.

The patient data used in this study was from an academic, urban, high-acuity hospital. There were over 2,500 patients in the system during the time period simulated, of which 771 were admitted from the ED, 367 were urgent admissions, 680 were elective patients, 290 were transfer patients, and 412 patients were admitted prior to the simulated month and thus occupied beds at the start of the model. Patient data was evaluated for the social and clinical eligibility criteria presented in Chapter 3. Summary statistics are provided in Table 12 regarding how the patient population sample matches the home hospital criteria. Further, 19.4 percent of the patients with the suitable home hospital illnesses of CAP, Cellulitis, CHF, COPD, and DVT required an ICU bed during their hospital visit.

Table 12 Summary statistics for percentage of patients meeting home hospital criteria

Admission Type	Age	Catchment	Community Referral	Hospital LOS	Suitable Illness
ED	100%	63.6%	0.4%	60.4%	9.3%
Urgent	100%	26.2%	67.2%	55.2%	5.4%
Elective	100%	28.6%	8.8%	70.5%	1.1%
Transfer	100%	26.6%	0.0%	35.9%	4.0%

Various simulation models were investigated to quantify the impact that home hospital may have on ED boarding in the existing system. Therefore we simulate five models of the case hospital, titled as follows in Table 13.

Table 13 Hospital models simulated for comparison

Model 1	Baseline Model: no home hospital incorporated
Model 2	ED Referral Model: admission to home hospital from ED
Model 3	Inpatient-Transfer Referral Model: admission to home hospital after initial stay in hospital inpatient bed
Model 4	Community Referral Model: admission to home hospital from physician office or clinic
Model 5	Fully Integrated Model: incorporation of ED Referral, Inpatient-Transfer Referral, and Community Referral models

Scenario 1 Results

This section evaluates the models for Scenario 1, as described in Chapter 4. Scenario 1 utilizes a freed inpatient bed from a home hospital admission to improve patient flow by making the bed available for the next ED, elective, urgent, or transfer patient requesting a bed in the floor unit. Each of the home hospital simulation models was run with the low, most likely, and high levels for clinical eligibility rates regarding home hospital admission, as presented in Chapter 3. The simulations are replicated 30 times for each month-long period. The parameter values and calculated means are presented in Table 14.

Table 14 Mean weekly ED boarding hours for simulated models for Scenario 1 (hours)

	Clinical Eligibility Rates Used	Week 1	Week 2	Week 3	Week 4	Avg. Boarding hrs. per Week	Avg. Patients to Home Hospital
Model 1: Baseline	Low	449.04	481.69	579.52	407.90	479.54	n/a
	Most Likely	449.04	481.69	579.52	407.90	479.54	n/a
	High	449.04	481.69	579.52	407.90	479.54	n/a
Model 2: ED Referral	Low	444.67	482.36	576.87	410.48	478.59	0.29
	Most Likely	440.56	485.55	579.83	413.00	479.73	0.43
	High	434.02	478.33	571.93	407.94	473.05	0.67
Model 3: IP-T Referral	Low	445.46	483.06	572.49	403.85	476.22	1.09
	Most Likely	442.63	478.78	573.00	405.64	475.01	1.61
	High	443.08	471.58	571.90	397.74	471.08	2.43
Model 4: Community Referral	Low	452.02	477.28	578.27	409.92	479.37	0.08
	Most Likely	453.88	476.68	570.76	408.65	477.49	0.13
	High	449.01	483.51	571.79	406.20	477.63	0.21
Model 5: Fully Integrated	Low	438.01	481.40	479.64	408.26	476.83	1.22
	Most Likely	436.45	478.82	576.84	399.93	473.01	1.66
	High	423.74	472.03	569.03	396.66	465.37	2.54

A paired t-test was utilized to compare the results in the models for before and after home hospital implementation at the 0.05 level. The paired t-test is employed to test

the mean difference between dependent or paired observations, where each observation in one sample is closely related or matched to an observation in the second sample (Hines, Montgomery et al. 2008). Alternatively, the paired t-test can be used when testing between different items subject to the same unique condition.

To assess the impact of home hospital on a hospital system's ED boarding, the weekly boarding rates were evaluated for home hospital models against the baseline model without home hospital. Weekly boarding tallies offer characteristic ED boarding rates experienced in a hospital system, as opposed to variable rates from day to day. The case model's empirical boarding rates support the weekly tallies, as each week of empirical data illustrate the variation that can be present in a single ED system. The case hospital's weekly boarding rates range between 415.7 and 567.1 hours per week, and are presented in Figure 16.

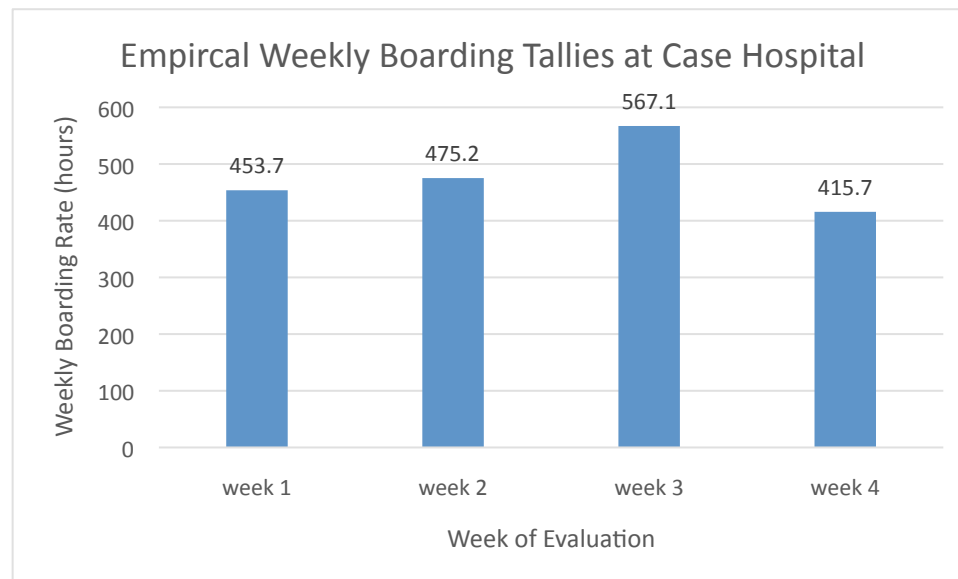


Figure 16 Empirical weekly boarding rates at case hospital

Each four-week-long simulation model is run 30 times, and an average weekly boarding rate is computed. The average weekly boarding rate of each home hospital model is used to compare against the average weekly boarding rate from the baseline model. The null hypothesis for the paired t-test states that the difference between the mean weekly boarding hours in a home hospital model and the mean weekly boarding

hours in the baseline model are zero. The alternative hypothesis states that the difference between the mean weekly boarding hours in a home hospital model and the mean weekly boarding hours in the baseline model are less than zero. The hypotheses are listed below, and the results of the paired t-tests at the 0.05 level are provided in the table below. Let the subscript i represent the model number as given in Table 13. Let j represent the scenario as given in Chapter 4.

$$H_0: \mu_{home\ hosp.\ model\ i, j} - \mu_{baseline\ model\ 1, j} = 0$$

$$H_1: \mu_{home\ hosp.\ model\ i, j} - \mu_{baseline\ model\ 1, j} < 0$$

A p-value below 0.05 allows one to reject the null hypothesis, and conclude that the difference between the mean boarding hours in the home hospital model and the mean in the baseline model is significantly less than zero at the 0.05 level. The paired t-test results are presented in Table 15.

Table 15 Paired t-test results between baseline and home hospital simulations

	Clinical Eligibility Rates Used	Test	Mean Difference (hrs)	p-value
Model 2: ED Referral	Low	$\mu_{2,1} - \mu_{1,1} = 0$	-0.94	0.265
	Most Likely	$\mu_{2,1} - \mu_{1,1} = 0$	0.19	0.539
	High	$\mu_{2,1} - \mu_{1,1} = 0$	-6.48	0.010
Model 3: IP-T Referral	Low	$\mu_{3,1} - \mu_{1,1} = 0$	-3.32	0.081
	Most Likely	$\mu_{3,1} - \mu_{1,1} = 0$	-4.53	0.060
	High	$\mu_{3,1} - \mu_{1,1} = 0$	-8.46	0.002
Model 4: Community Referral	Low	$\mu_{4,1} - \mu_{1,1} = 0$	-0.16	0.466
	Most Likely	$\mu_{4,1} - \mu_{1,1} = 0$	-2.04	0.160
	High	$\mu_{4,1} - \mu_{1,1} = 0$	-1.90	0.136
Model 5: Fully Integrated	Low	$\mu_{5,1} - \mu_{1,1} = 0$	-2.71	0.133
	Most Likely	$\mu_{5,1} - \mu_{1,1} = 0$	-6.53	0.009
	High	$\mu_{5,1} - \mu_{1,1} = 0$	-14.17	0.000

As presented in the table, four of the paired t-tests generate p-values less than 0.05, signifying that there is evidence to conclude that the mean of the corresponding home hospital models in these tests are less than the baseline model at the 0.05 level of significance. These models whose means are significantly less than the mean of the baseline model at the 0.05 level are: ED Referral with High eligibility, Inpatient-Transfer Referral with High eligibility, and the fully integrated models with Most Likely and High eligibilities. Additionally, the Inpatient-Transfer Referral models with Low and Most Likely eligibilities reject the null hypothesis at the 0.10 level.

Of the models whose average weekly boarding rates significantly differed from the baseline, the fully integrated model with high eligibility had the largest savings in

boarding hours with a three percent decrease from the baseline. The least savings of the models with significant differences was the ED Referral Model with High eligibility employed, which resulted in a decrease of 1.4 percent from the baseline.

Low vs. Most Likely Clinical Eligibility Results

The results in Table 14 present comparable average weekly boarding hours between the Low and Most Likely clinical eligibility cases. In fact, Model 2 results in a slightly lower boarding average for the Low eligibility case than the Most Likely. This seems counterintuitive considering more patients are admitting to home hospital in the Most Likely cases. A paired t-test between the cases resulted in a p-value of 0.520 and signifies that there is no evidence to conclude that the means are significantly different from each other at the 0.05 level.

Regarding Model 2, the biggest impact on boarding from home hospital came in week 1, as the Low eligibility case admitted an average of 0.64 patients to home hospital per week and the Most Likely case admitted an average of 1.33 patients. The remaining three weeks for the Low case averaged only 0.06 patients per week. The Most Likely case averaged 0.12 patients per week for the remaining three weeks. These low admission numbers to home hospital during these weeks are driven by the fact that very few patients met initial eligibility and selection criteria: LOS less than five days, non-ICU bed request criteria, has a suitable home hospital illness, lives within the catchment area, and admits during the hours of home hospital operation. Two patients met all of these criteria during the first week; only one patient met all of the criteria during each of the second and third weeks; no patients met the criteria during the fourth week. Therefore it makes sense that the first week sees a lower boarding rate in the ED Referral Models than the baseline, and specifically a four hour better boarding rate for the Most Likely case versus the Low case. Meanwhile, the remaining three weeks for both eligibility cases bounce slightly above and below the baseline results. The lack of home hospital patients

admitted during the second, third, and fourth weeks help explain why boarding rates are so similar between the Low and Most Likely cases for the ED Referral Models. The low admission numbers indicate home hospital did not play a significant role in affecting the boarding hours during these three weeks. The variation each week between the two cases, and perhaps the reason why the Low case ends up with a slightly lower overall average boarding rate, can likely be attributed to other probabilistic variability in the bed assignment process, such as the bed cleaning turnaround delays, the Bed Placement Task delays, and the Nurse Report Task delays.

Number of Patients Admitted from Model Types

Two-thirds of the patients presenting to the hospital with a suitable home hospital illness came from the ED, while the remaining one-third of patients with one of the five illnesses admitted as urgent, elective, and transfer patients. However, the ED Referral models each admitted a fraction of the patients per week as the corresponding Inpatient-Transfer Referral models. Further as presented in Table 12, ED patients compared favorably in social eligibility criteria such as living within the catchment area, age, and LOS. The limitations that the ED referral model presents, however, restricted potential home hospital patients from admission. The ED referral models allowed admission to home hospital between the typical home hospital hours of 8:00 am to 6:00 pm, similar to hours operated in past research and current working programs. However many ED bed requests at the case hospital occurred after the 6:00 pm close time, as illustrated in Figure 17. Less than 35 percent of bed requests from the ED occurred during the daily ten hour timeframe for which home hospital was open in the model. Patient arrivals to the ED often peaked in the mid-to-late afternoons at the case hospital, and home hospital evaluation and admission preparation often occurs before an ED patient's care is complete. However, bed request time from the ED in this study represents when a patient's care in the ED is complete, and therefore when a patient would be ready for

transfer to home hospital admission. Often the time of bed request occurred after the close of home hospital operation.

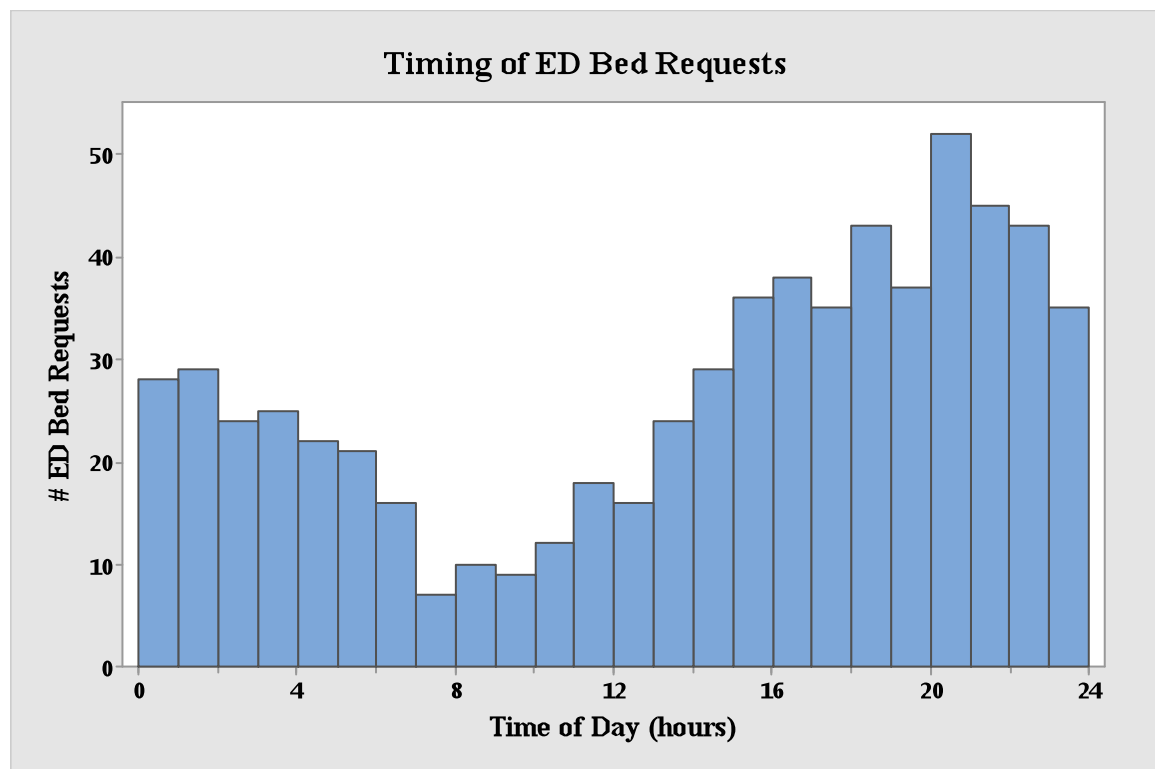


Figure 17 Timing of ED bed requests for month

On the other hand, the Inpatient-Transfer Referral models incorporated the flexibility for a patient to potentially be admitted to home hospital regardless of the time of day of admission to the hospital. In the Inpatient-Transfer models, if an ED patient requested a hospital bed after the close of home hospital operation hours, the patient was admitted to a hospital bed for at least 24 hours, and so was transferred to home hospital the following day. This flexibility allowed additional patients to be admitted for Model 3 as compared to Model 2, as presented in Table 14. Many of these additional patients that were transferred to home hospital in the inpatient-transfer models were patients admitted from the ED. For example, 90 percent of the average number of patients admitted to home hospital each week through Model 3 with Most Likely eligibility rates initially presented to the facility through the ED before admitting to a hospital bed and eventually transferring to home hospital.

Timing of Boarding Impact by Home Hospital

As a part of the results, we also analyzed the influence of home hospital on ED boarding hours by the time of day. Figure 18 illustrates average hourly boarding times experienced for the baseline model versus the fully integrated home hospital model (with High clinical eligibility rates utilized). The case hospital ED experiences a trend in boarding throughout a day, similar to the trends that most hospital EDs experience (Shi, Chou et al. 2012). With the common issue of existing inpatients typically occupying beds until the afternoons and evenings before discharge, the case hospital ED experiences a surge in average boarding times for patients in the mornings. The average boarding rate then steps down slightly in the afternoon, and gradually declines through the evening as inpatient beds free up. Figure 18 also illustrates times in the day where the average hourly boarding times differ between the baseline and home hospital model. Between the 14 and 18 hours, we see the most significant differences between the boarding rates. The home hospital model has an average boarding time for patients requesting beds in the 15 hour of 4.68 hours, versus an average of 5.26 hours in the baseline model. This represents about a 35 minute, or eleven percent, decrease in average boarding time, and happens to occur at a time when the ED is typically getting to be at its busiest in terms of patient arrivals in the mid-afternoon. The average boarding times for other hours during the day are very close to the baseline results.

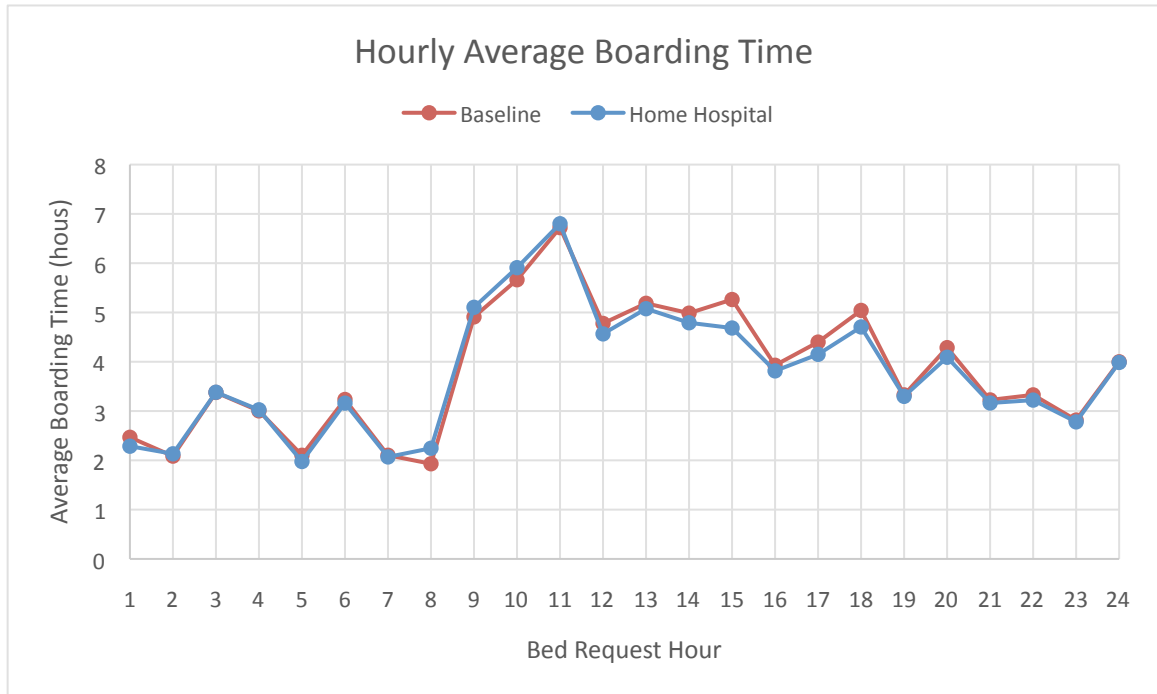


Figure 18 Average hourly boarding times of baseline and fully integrated home hospital (High eligibility) simulation outputs

In addition to evaluating boarding impact by hour of day, we also assessed boarding with respect to the timing of home hospital admission days. Figure 19 illustrates hourly average boarding times for days which patients were admitted to home hospital for baseline and fully integrated home hospital models with High eligibility utilized. The average boarding time per bed request hour on days which patients were admitted to home hospital was 4.30 hours, versus 4.37 hours for the same days in the baseline model without home hospital, accounting for a decrease of 1.6 percent. However, no significant gaps are recognized between the plotted hourly boarding times for each model in Figure 19. When compared with Figure 18's more noticeable improvements between the 14 and 18 hours, it becomes apparent that home hospital can have a significant impact on boarding in ensuing days after a home hospital admission occurs. Specific to Scenario 1 models tested, the freed bed hours from home hospital admission work to decrease bed occupancy and can improve patient flow to allow ED admits and other patient types occupy beds earlier in ensuing days. Assuming patient

length of stays remain the same regardless of an earlier bed assignment, this bed flow support is expected to be at hand until the original home hospital patient's length of stay is complete. At that time, the system would resort back to the baseline bed demand state.

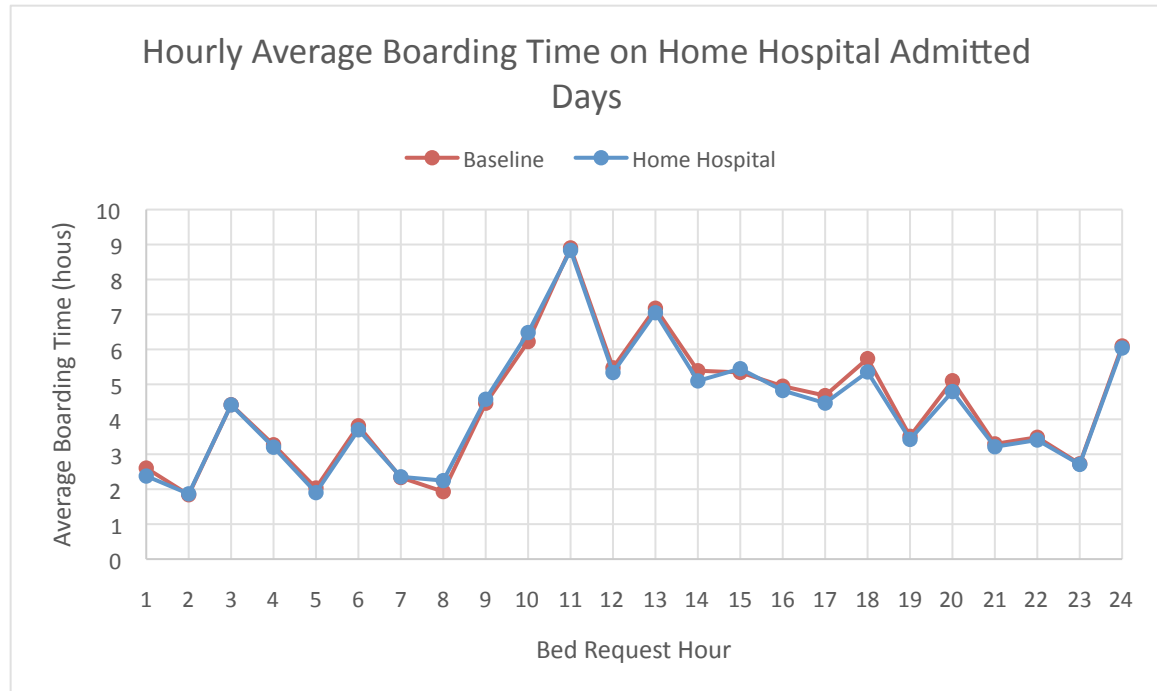


Figure 19 Average hourly boarding times for days with home hospital admissions for baseline and fully integrated home hospital (High eligibility) simulation outputs

Boarding Impact per Home Hospital Admission

The simulation tests allow a comparison of boarding impact per home hospital admission between model types. This gives a sense of a home hospital admission's strength to influence boarding. Of the models with significant differences in boarding with the baseline, the ED Referral Model with High eligibility rates had the highest average boarding decrease per admitted home hospital patient, at 9.69 decreased boarding hours per patient. The second highest was from the fully integrated model with High eligibility, at 5.58 hours per admitted home hospital patient. The lowest impact per admitted patient occurred in the Inpatient-Transfer model with High eligibility, 3.48 hours per patient. These boarding hours per admitted patient are not the saved hours from the patient alone, but saved hours in the ED system as a whole.

While the ED referral models result in smaller overall decreases of boarding hours than the fully integrated and inpatient-transfer models, the ED referral model stands as the most direct impact to influencing boarding per patient. In addition to improving patient flow by freeing an inpatient bed, an ED patient admitted to home hospital also often directly affects the boarding that this patient experiences otherwise. Unless a patient in the baseline model has a short boarding time in the neighborhood of the Home Hospital Referral Task delay (between zero and two hours), the ED patient should see direct savings in boarding for the home hospital admission case. The fully integrated model also takes advantage of the direct savings of ED referrals to home hospital, however additional patients can also be admitted through inpatient-transfer and community referral. The referral sources do not guarantee an impact on ED boarding rates, as boarding hours are not directly influenced from an admission to home hospital. Instead, these referral sources must rely on freed inpatient bed hours to help improve patient flow, and that an ED bed request is made for the same floor unit. The Inpatient-Transfer Referral model has the least impact per patient from our simulation results.

Scenario 2 Results

This section evaluates the results for Scenario 2, as described in Chapter 4. Scenario 2 represents if the freed inpatient bed hours saved from home hospital admissions are reserved for use as hospital leaders see fit with respect to hospital organizational goals. The freed bed hours would not be used to improve patient flow; a freed bed would not be assigned to a patient requesting a bed from the ED. This scenario represents a hypothetical condition in which hospital leaders may want to use the additional bed hours for other purposes or additional patients. For example, these bed hours could be used to admit additional high revenue elective patients.

The bed hours saved from home hospital admissions is calculated by taking the difference between the patient's actual discharge time from the data and the patient's

average time of admission to home hospital from the simulation runs. The time of admission to home hospital indicates the time which the patient exits the hospital facility, and therefore when the bed may be used in another capacity. After simulating each of the models for 30 replications, the expected average saved bed hours per week are presented in Table 16. The fully integrated home hospital model generated the most freed bed hours; utilizing the high clinical eligibility rate resulted in an average of 124.51 bed hours per week. The model saving the next largest average of weekly boarding hours was the Inpatient-Transfer Referral Model, with 97.58 hours freed using the high eligibility rate.

Table 16 Saved bed hours from home hospital implementation in Scenario 2

	Clinical Eligibility Rates Used	Average Hours per Week
Model 2: ED Referral	Low	14.00
	Most Likely	22.43
	High	37.86
Model 3: IP-T Referral	Low	44.51
	Most Likely	58.17
	High	97.58
Model 4: Community Referral	Low	5.35
	Most Likely	8.91
	High	15.04
Model 5: Fully Integrated	Low	58.04
	Most Likely	81.13
	High	124.51

The saved bed hours presented in this section occur throughout a week, and are not single blocks of time of freed beds. They are the average weekly number of bed hours that are no longer used if a patient is admitted to home hospital in the model. These hours are aggregated from our model, which keeps all other bed request times for elective patients the same as empirically observed. This suggests that if the timing of

elective bed demand were rescheduled to take advantage of the freed bed hours, other additional patients may be able to be treated.

Scenario 3 Results

This section evaluates the results of models for Scenario 3, as described in Chapter 4. Scenario 3 represents a hybrid model for how any freed inpatient bed hours saved from home hospital admissions are utilized. Scenario 3 randomly assigns half of saved bed hours to remain open for improved bed flow and a reduction in ED boarding hours, while the other half of saved bed hours are reserved for use as hospital leaders see fit with respect to hospital organizational goals. This scenario represents a hypothetical condition in which hospital leaders may want to utilize some saved bed time for improved flow and some to be used as additional bed hours for other purposes or additional patients.

The bed hours saved from home hospital admissions is calculated in the same manner as described for Scenario 2 above: taking the difference between the patient's actual discharge time from the data and the patient's average time of admission to home hospital from the simulation runs. After simulating each of the models for 30 replications, the expected average weekly boarding hours, average number of patients admitting to home hospital, and average saved bed hours per week are presented in Table 17. The fully integrated home hospital model resulted in the least average boarding hours per week, the most patients admitted to home hospital per week, and generated the most freed bed hours when utilizing the high clinical eligibility rate.

Table 17 Mean weekly ED boarding hours for simulated models for Scenario 3 (hours)

	Clinical Eligibility Rates Used	Week 1	Week 2	Week 3	Week 4	Avg. Hours per Week	Avg. Patients to Home Hospital	Avg. Bed Hours Saved per Week
Model 2: ED Referral	Low	447.37	479.27	578.56	402.24	476.86	0.16	8.64
	Most Likely	448.38	478.06	579.40	402.87	477.17	0.24	12.74
	High	443.49	476.37	580.90	410.45	477.80	0.32	17.96
Model 3: IP-T Referral	Low	445.65	483.24	581.02	398.96	477.92	0.62	21.45
	Most Likely	449.75	476.85	577.05	405.02	477.17	0.78	30.01
	High	447.57	477.55	573.30	409.05	476.87	1.2	50.37
Model 4: Community Referral	Low	451.90	475.87	577.50	410.51	478.94	0.04	2.78
	Most Likely	454.63	478.82	571.18	407.41	478.01	0.05	3.34
	High	450.63	476.90	576.95	412.46	479.20	0.09	6.13
Model 5: Fully Integrated	Low	442.23	482.51	570.41	405.85	475.25	0.69	29.76
	Most Likely	442.35	479.41	574.67	404.30	475.30	0.82	35.93
	High	439.80	478.48	571.51	406.50	474.07	1.34	65.41

Again a paired t-test was utilized to compare the results in the models for before and after home hospital implementation at the 0.05 level. The average weekly boarding rate of each home hospital model was used to compare against the average weekly boarding rate from the baseline model. The null hypothesis for the paired t-test states that the difference between the mean weekly boarding hours in a home hospital model and the

mean weekly boarding hours in the baseline model are zero. The alternative hypothesis states that the difference between the mean weekly boarding hours in a home hospital model and the mean weekly boarding hours in the baseline model are less than zero. The hypotheses are listed below, and the results of the paired t-tests at the 0.05 level are provided in Table 18. Let the subscript i represent the model number as given in Table 13. Let j represent the scenario as given in Chapter 4.

$$H_0: \mu_{\text{home hosp. model } i, j} - \mu_{\text{baseline model } 1, j} = 0$$

$$H_1: \mu_{\text{home hosp. model } i, j} - \mu_{\text{baseline model } 1, j} < 0$$

A p-value below 0.05 allows one to reject the null hypothesis, and conclude that the difference between the mean boarding hours in the home hospital model and the mean in the baseline model is significantly less than zero at the 0.05 level. The paired t-test results are presented in Table 18.

Table 18 Paired t-test results between baseline and home hospital simulations for Scenario 3

	Clinical Eligibility Rates Used	Test	Mean Difference (hrs)	p-value
Model 2: ED Referral	Low	$\mu_{2,1} - \mu_{1,1} = 0$	-2.28	0.147
	Most Likely	$\mu_{2,1} - \mu_{1,1} = 0$	-2.36	0.179
	High	$\mu_{2,1} - \mu_{1,1} = 0$	-1.74	0.264
Model 3: IP-T Referral	Low	$\mu_{3,1} - \mu_{1,1} = 0$	-1.84	0.186
	Most Likely	$\mu_{3,1} - \mu_{1,1} = 0$	-2.36	0.115
	High	$\mu_{3,1} - \mu_{1,1} = 0$	-2.20	0.198
Model 4: Community Referral	Low	$\mu_{4,1} - \mu_{1,1} = 0$	-0.59	0.382
	Most Likely	$\mu_{4,1} - \mu_{1,1} = 0$	-1.52	0.206
	High	$\mu_{4,1} - \mu_{1,1} = 0$	-0.33	0.414
Model 5: Fully Integrated	Low	$\mu_{5,1} - \mu_{1,1} = 0$	-4.29	0.013
	Most Likely	$\mu_{5,1} - \mu_{1,1} = 0$	-4.23	0.024
	High	$\mu_{5,1} - \mu_{1,1} = 0$	-5.47	0.027

As presented in the table, three of the paired t-tests generate p-values less than 0.05, signifying that there is evidence to conclude that the mean of the home hospital models in these tests are less than the baseline model at the 0.05 level of significance. The models whose means are significantly less than the mean of the baseline model at the 0.05 level are: the fully integrated models with low, most likely, and high eligibilities.

Results on Patient Groups

This section evaluates results of home hospital's impact on patient groups within the patient population at the case hospital. The ED observation patients and the clinical decision unit (CDU) patients are evaluated. Observation patients are patients expected to have a short length of stay in the hospital. The CDU is an observation unit within the ED

which provides physician care and observation services which goes beyond the initial evaluation and management of care provided in the ED. These individuals are less sick patient groups with shorter length of stays. Both groups are potential home hospital targets regarding these criteria.

Observation Patients

Observation patients are defined as patients requiring ongoing short-term care and assessment to determine whether further treatment will be needed as an inpatient or if the patient can be discharged from the hospital (Health and Services 2004). Observation status can be assigned to elective, urgent, and ED patients, and are often expected to have a short LOS as an observation patient in the hospital, often between one to three days. In our case hospital, about 26 percent of observation patients who admitted to the hospital during the evaluation period were admitted from the ED. Of these patients from the ED, about 70 percent came from the CDU.

Of the 73 observation patients evaluated at the case hospital who were from the ED, only one presented with a home hospital suitable illness as the primary diagnosis. Similarly of the 148 elective patients with observation status, only one patient presented with a home hospital suitable illness as the primary diagnosis. None of the urgent patients with observation status presented with a home hospital suitable primary diagnosis. The simulation model results were evaluated, and no observation patients were admitted to home hospital.

Findings from Other Home Hospital Program Scenarios

To obtain more insights into the impact that a home hospital program may have on ED boarding performance, other hypothetical scenarios are tested for the case hospital. Home hospital clinical trials from past research and current ongoing home hospital programs have differed from one another. Over the years, they have changed, evolved,

and taken on various philosophies for how to run each program. Different groups have selected different types of suitable illnesses, age ranges for qualified individuals, catchment areas of patient residences, referral sources for remote care, hours of operation for the programs, and staffing schemes. Besides the home hospital program being implemented, there are also differences between the makeups of hospital organizations. Even within urban academic hospitals, differences can be experienced amongst various patient mixes, varying degrees of existing crowding and occupancy levels, and partnerships or cooperation with community clinics. This section presents scenarios to test cases where: 1) home hospital program implementation is varied from traditional operation hours; 2) low and high hospital crowding levels are tested for home hospital's impact on ED boarding.

Home Hospital Implementation Timing

To gain insight into how the timing of implementing home hospital throughout a week impacts crowding, we test the model without the limitation of typical hours of operation for home hospital. This test evaluates the relationship between when ED arrivals and the hours of operation for a home hospital program. There are seemingly clear reasons why manageable hours of operation have been employed in past home hospital programs, such as staffing concerns, safety of caregivers, and difficulty in procuring and delivering equipment and medical supplies. However in a crowded, urban hospital facility, demand for bed requests from ED patients can occur later into the evenings and nighttime hours. Figure 17 illustrates the time of day that bed requests were made throughout the month-long evaluation period at the case hospital. The peak for when the most bed requests were made occurred well after the 6:00 pm close of a typical home hospital program. Therefore we test a home hospital program with a 24 hour operation schedule to assess the impact that bed request timing and the hours of home hospital operation have on ED boarding.

The simulation was run for two home hospital program types: Model 2 and Model 5, from Table 13. Model 2, the ED Referral Model, was tested due to the significant number of bed requests that occurred after the close of traditional home hospital hours. Model 5, the fully integrated home hospital model, was also tested to evaluate any trickledown effect through the other admission sources.

The ED Referral Model was simulated utilizing the Most Likely clinical eligibility rates for the five suitable home hospital models. No limits on time of day were imposed. The simulation resulted in an average weekly boarding rate of 469.51 hours. This gives an expected weekly savings of over 10 hours per week when compared to the 479.73 hour mark in Table 14 for the ED Referral Model with Most Likely eligibility with traditional 8:00 AM to 6:00 PM hours of operation. Further, 1.48 patients are expected to be admitted to home hospital per week and 93.49 bed hours are expected to be saved without the operating hours limitation, versus 0.43 patients and 22.25 hours respectively.

The simulation was also run for Model 5, a fully integrated home hospital model, utilizing the Most Likely clinical eligibility rates for the five suitable home hospital models. No limits on time of day are imposed. The simulation resulted in an average weekly boarding rate of 465.74 hours. This gives an expected weekly savings of a little over four hours per week when compared to the 470.12 hour mark in Table 14 for the fully integrated model with Most Likely clinical eligibility employed with traditional 8:00 AM to 6:00 PM hours of operation. Further, 2.08 patients are expected to be admitted to home hospital per week and 132.96 bed hours are expected to be saved without the operating hours limitation, versus 1.76 patients and 81.13 hours respectively.

The simulation tests without operating hours limitations allows a comparison of boarding impact per home hospital admission between the ED Referral Model with Most Likely eligibility rates without operating hours limitations and the Inpatient-Transfer Model with Most Likely eligibility rates.

Hospital Crowding Levels

In our simulation experiments, we test how home hospital's impact on ED boarding varies with various crowding levels experienced in the hospital system. The case hospital is typically a high occupancy inpatient facility, with an average midnight occupancy of about 89.2 percent during the evaluation period. The national average for hospitals of similar bed size is 74 percent. Therefore we test our case hospital for ED boarding results when an average occupancy rate of 74 percent is targeted; this model is titled the Low Occupancy Model. To round out this sensitivity analysis, we also test for an extreme case of crowding in the hospital with an average occupancy rate target of 93 percent, and the model is titled High Occupancy Model. We test the fully integrated home hospital model (Model 5) with Most Likely clinical eligibility rates against our baseline model with the corresponding occupancy rates. The fully integrated home hospital model is the model assessed in order to evaluate a system which emphasizes home hospital admission through the various referral modes.

The baseline Low Occupancy Model resulted in an average midnight occupancy of 74.4 percent, as opposed to the fully integrated home hospital (Model 5) Low Occupancy Model of 74.6 percent. Average weekly boarding hours between the baseline and home hospital models were similar, 238.26 and 235.19 hours respectively. The difference represented a 1.3 percent decrease, compared to the two percent decrease in boarding hours between the models with existing occupancy levels at the case hospital (see Table 14). Regarding the High Occupancy models, the average midnight occupancy rates were comparable at 93.4 percent for the baseline and 93.8 percent for Model 5. Average weekly boarding hours between the baseline and home hospital models were also similar, 1476.99 and 1427.98 hours respectively. This difference represented a 3.3 percent decrease using the home hospital program, as compared to the two percent decrease for the existing occupancy at the case hospital, as presented in Table 14. See Table 19 for results from the crowding level tests.

Table 19 Mean weekly ED boarding hours for crowding level simulation tests

	Clinical Eligibility Rates Used	Avg. Occupancy at Midnight	Avg. Boarding Hours per Week	Percent Change
Baseline, Low Occupancy Model	n/a	74.4%	238.26	n/a
Model 5, Low Occupancy Model	Most Likely	74.6%	235.19	1.3%
Baseline, High Occupancy Model	n/a	93.4%	1476.99	n/a
Model 5, High Occupancy Model	Most Likely	93.8%	1427.98	3.3%

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

This chapter summarizes the steps taken in this study. Then the major findings reviewed. Discussion of the conclusions are presented. Future work is described.

This study examined the relationship between home hospital care and ED crowding performance at a large, urban, teaching hospital facility. Home hospital care was characterized and established for the scope of this study with respect to impacts on hospital patient flow. A methodology for identification of potential home hospital patients was employed through clinical and social criteria, and a scale for the range of clinical eligibility rates was established for the five suitable illnesses. The study modeled patient flow and bed demand, and used computer simulation modeling to evaluate the impacts of home hospital care on ED boarding performance. Various models incorporating home hospital were simulated through an ED Referral program, Inpatient-Transfer Referral program, Community Referral program, and a fully integrated home hospital program. Three scenarios were run for each model to assess practical possibilities for the utilization of the freed bed hours from a home hospital program.

The results of this analysis reveal the association between home hospital care and ED boarding performance. The study setting of a large, urban, teaching hospital offers a specific patient mix. A reasonable cohort of patients met certain social and clinical eligibility criteria, such as age requirements, living within catchment areas, and having moderate length of stays. However, many patients who presented to the case hospital were also often very sick, requiring ICU beds or presenting with multiple illnesses.

From our Scenario 1 simulation tests, not surprisingly the Fully Integrated home hospital model (Model 5) was the most impactful type of home hospital program on ED boarding. Incorporating all methods of home hospital referral (ED, inpatient-transfer,

and community), the Fully Integrated model resulted in statistically significant boarding tallies that were less than our baseline model for the Most Likely and High clinical eligibility rate cases. The tests' largest average decrease in boarding hours came from the Fully Integrated model and was about 14 hours per week, or about a 3 percent decrease. The average weekly boarding hours for the ED Referral and the Inpatient-Transfer models with High eligibility also were significantly less than the baseline boarding rates. The Community Referral model failed to make a significant impact on boarding as a standalone home hospital program.

The Fully Integrated and Inpatient-Transfer models reached average weekly patient admissions of about 2.5 with High clinical eligibility employed. This extrapolates to about 10 admissions per month and 120 per year. The ED Referral and Community referral models admitted far fewer patients to home hospital than the inpatient-transfer mode. However, each patient admitting to home hospital from the ED may have a larger impact on ED boarding rates, than those of an inpatient-transfer program. An ED referral to home hospital will directly impact the boarding time of that patient, whereas an inpatient-transfer could result in benefitting patient flow for other patient types depending on who requests beds in the free bed's ward.

In this study's Scenario 2 tests, the average number of bed hours saved per week with home hospital is calculated. The results provide a range for the potential boarding hours saved at the case hospital. The Fully Integrated model with High eligibility saves an average of 124.51 bed hours per week. Based on the case hospital's average length of stay of about 6.5 days, the bed hours for almost one additional patient per week would be saved. If Low eligibility is employed, the fully integrated model averages a savings of 58 bed hours per week.

Discussion

The results of our simulation model tests give a range of boarding hours among the different models and clinical eligibility rates. These clinical eligibility rates were established based on published research studies and industry expertise for a wide range of hospital settings. Our large, urban, academic hospital setting is a highly specialized care-provider and serves a high acuity patient mix. Therefore, the High clinical eligibility rate would likely be inappropriate to identify the patients at the case hospital. Conservatively, we could also use the same logic to reason that the Most Likely eligibility may not be suitable either. Still, the various eligibility rates are established and evaluated as a sensitivity analysis. However, all models using Low eligibility rates in our study resulted in insignificant differences from the baseline boarding rate.

Upon evaluation of the results using Most Likely and High rates, while the differences are statistically significant from the baseline in some of these tests, the differences are not necessarily practically significant. Evaluating the most impactful case of the fully integrated home hospital model with High eligibility, the average weekly three percent decrease in boarding rates may not make a practical difference within the emergency department system. The 14 hour boarding decrease may not change or influence the way hospital leaders operate and run the ED.

Access to Home Hospital Care

In our Scenario 1 simulation tests, it became apparent that the Inpatient-Transfer referral mode allowed the greatest flexibility and opportunities for patients to admit to home hospital, and the ED Referral model had a few constraints. ED referral often had very low admission numbers per week due to the mismatch of when ED patients requested admission to the hospital and the hours of operation of home hospital. Our hypothetical simulation test for a home hospital program operating 24 hours per day

illustrates how the implementation timing restricts admissions. Model 2 saw the average number of weekly admits more than triple from 0.42 to 1.48 patients. Further, the ED Referral model did not allow any flexibility in how or when patients could admit to home hospital. If the patient needed an ICU bed or if length of stay was greater than five days (i.e. patient was very sick), the patient was immediately deemed ineligible for home hospital and admit to an inpatient ward. The Fully Integrated and Inpatient-Transfer models on the other hand incorporated multiple opportunities for individuals to admit to home hospital. If eligibility was not met upon presenting to the hospital, eligibility was reassessed upon a bed transfer (i.e. ICU bed to non-ICU floor bed). If the patient presented at a time when home hospital was not operating, the patient would be admitted to an inpatient bed and transferred to home hospital the following day when the home hospital program reopened.

The simulated models incorporating inpatient-transfer reached average weekly patient admissions of about 2.5 with High clinical eligibility employed in our tests. This extrapolates to about 10 admissions per month and 120 per year. This is a realistic program volume, as the Portland VA Medical Center operated a fully integrated home hospital program in 2008 which had a staff support capacity of 120 patients. The Portland program grew to admitting over 160 patients by 2011. The team at the Portland VA estimated the financial breakeven point for supporting the home hospital program infrastructure to be about 78 admissions (Home 2008).

On the other hand, the maximum numbers of admissions resulting from our analysis for ED Referral and Community Referral models was 0.67 and 0.21 patients per week. The low admission numbers are likely due to the high acuity patient mix that our urban, teaching case hospital serves. About one-third of ED patients who admitted to the case hospital with a suitable home hospital illness were ineligible for home hospital due to excessive length of stays. Slightly less than 20 percent of ED patients with a suitable

illness were determined ineligible due to the requirement of an ICU bed. These findings may not be generalizable to other hospital settings with less sick patients.

Bed Resources and Capacity

In this study's Scenario 2 tests, the average number of bed hours saved per week with home hospital is calculated. The hours saved depended on the number of patients admitted to home hospital and how early into the inpatient stay the individual was transferred home. As mentioned before, how the saved bed hours are used can be decided upon by hospital leadership. If bed demand in the system stays consistent with the empirical data, the saved bed hours can be used to improve patient flow for other patients requesting beds in the bed ward. Otherwise the saved bed hours could potentially be applied to new, additional patients. If the home hospital patient is receiving care and a new additional patient is admitted, this option works to allow the hospital organization an extra bed for patient capacity.

This concept of freeing a bed for an additional patient can be very valuable. Hospitals often are trying to implement less costly solutions to expanding capacity than traditional capital investment projects (Jack and Powers 2009). In some markets, the cost of constructing physical expansion space can cost around one million dollars per bed or more (Kirby and Kjesbo 2003), and operating costs per bed can be in the neighborhood of \$250,000 (of which 5-10 percent of which may be attributed to facility management costs) (Litvak 2010).

It should be noted that that using freed bed hours for additional inpatients may impede ED boarding improvements. Introducing new patients into the system is outside the scope of our models, but could cause higher boarding times for a new patient causing a mismatch between admissions and discharges.

Facility Management Implications

ED crowding can adversely impact the overall responsibility of the hospital to adequately care for the general public, and may trigger boardroom-level discussions concerning occupancy rate concerns, capacity, and growth of the facility. A potential strategic level facility management action is identified in the description above regarding the potential for a home hospital program to provide a financially strategic prospective capacity expansion method through freed inpatient bed hours. However the home hospital programs in this study resulted in low rates of potential bed capacity expansion, as seen in the simulation results of Scenario 2. Perhaps a more realistic perception of the repurposed bed hours from home hospital in this case is as an additional revenue stream for the hospital organization, rather than a bed expansion strategy.

This research concentrates more closely on the tactical level facility management focus of crowding. As discussed in Chapter 1, ED crowding can have numerous impacts on whether hospital facilities or staff work perform at desired levels, causes longer wait times for people to obtain care, and disrupts the operation of emergency medical services. In our study's case hospital setting, results do not produce significant and practical decreases on ED boarding rates through home hospital. However we see hints of larger potential impacts if under an alternate hospital setting, allowing for higher home hospital admission rates, such as a fully integrated home hospital program at a hospital serving a low acuity patient mix with short length of stays. With less ED crowding, there is the potential for improved tactical performance within the facility.

This study promotes the advancement of facility management research towards a strategic and highly analytical direction within the academic community and industry. The facility management discipline has traditionally been linked with operational activities within an organization. However this research study supports the growing understanding that facility management is important to and associated with strategic and tactical/performance-driven activities as well.

Limitations

This study used computer simulation to examine the complex relationship between home hospital and ED crowding. As with all modeling, limitations exist that must be considered with the results. The limitations are discussed in this section.

The simulation model developed in this study cannot realistically account for all potential scenarios. Probability distributions are employed for task delays, so it is possible for an outcome in reality to appear outside the range of our distributions. We analyzed the hospital for a four week period, and must state that the model we developed is a variation of the system during this time. Based on the assumption that the dataset resembles a typical month at the case hospital, the model is believed to represent and generate possible and realistic results. The arrivals, lengths of stay, and patient entity characteristics, such as illnesses and home hospital eligibility variables, in the model are a discrete, fixed set of data. Therefore while the model does not evaluate extensive variations in arrival patterns and patient mix possibilities, the model does allow for four distinct weeks to be evaluated for various home hospital impacts. So although data from other time periods, or even data from other hospitals, may experience differences in model setup and results, the operational insights and relations between home hospital and ED boarding analyzed in this study are believed to be broadly applicable.

The impacts to ED boarding by the applications of home hospital are based on certain assumptions, previous studies, and expert opinion. Therefore, the implementation of home hospital care in a real hospital system could result differently from our expected results.

Although existing home hospital programs are currently in practice in the U.S., it is not a widely used model of care throughout the country. There are concerns over reimbursement potential to bring in revenue, patient health and safety, and legal risk and protection. The scope of this study focuses on tactical performance of hospital facilities regarding ED crowding, and so does not include medical/clinical, legal, or economic and

payment evaluations of home hospital. But this study recognizes that while clinical and social home hospital research has been and continues to be conducted regarding these topics, there is still work to be done to make home hospital a widely used health care method in the U.S. For example while numerous studies have examined the quality of care of home hospital to be on par or better than inpatient hospital care (Leff, Burton et al. 2005, Mader, Medcraft et al. 2008, Leff, Burton et al. 2009, Shepperd, Doll et al. 2009a), both doctors and patients still have doubts or concerns. Further research, advances in innovative telemedicine equipment, policy and legislation change, and simply more time and comfort using remote care models may be needed to assure or satisfy skeptics. This study recognizes these reservations as existing obstacles to current widespread use of remote care. However with the existing research and functioning home hospital programs, they are seen as just obstacles, and not barriers. These reservations could be overcome via further research, healthcare policy changes, and time. The issues like reimbursements and patient care and safety are outside the scope of this study, as the focus here is on understanding the relationship between remote care and ED crowding. Therefore, this study is conducted under the assumptions that these obstacles to widespread use of home hospital will be or can be resolved, if they have not already.

Home hospital programs are reliant on an ample and capable nurse workforce to function and operate. Nurses could need to be skilled in various treatment types, and nurses may visit home hospital patients one to three times per day. Therefore available nursing staff may be a limiting factor in the number of patients a home hospital program can service. While directives, such as cross-use of an organization's existing homecare nurses and the policies in the Affordable Care Act, are working to increase the nurse workforce in the U.S. (Litvak and Bisognano 2011), this study assumes hospital organizations have access to the needed nursing staff to service all eligible and consenting home hospital patients.

Future Work

The simulation model and methodology proposed in this study can be used for other studies to build on the insights gained in this analysis. Multiple directions can be taken for future work.

While the scope of this study focuses around the tactical FM issue of ED crowding, the potential insights about home hospital and the home hospital modeling methods from this study could open the door to other aspects of facility management research. Researchers could possibly undertake studies shifting focus onto strategic FM activities. Home hospital could have the potential to influence functional capacity of facilities and capacity planning research, studies of economic evaluations for avoiding or reducing capital project and operating costs, or research regarding the market competition and maximization of revenue.

This study evaluated home hospital for only the five suitable illnesses found to be well documented in the clinical research with published eligibility rates. As clinical research progress, more illnesses can and should be incorporated into the study.

Considering the number of inpatient bed hours that can potentially be saved through home hospital, a stochastic model could be built to evaluate how additional patients added to the patient flow impact ED crowding. The data requirements for this study would be for a longer period of time at the hospital system than our study.

In this study, our focus is on home hospital's impact to ED boarding rates. However keeping in line with the saved hospital bed hours from home hospital admissions, a study can be conducted to assess improvements or impacts to patient flow for other patient types (elective, urgent, and transfer patients). Freed bed hours may lead to improvements in wait times for these patients. Data requirements for this study would need to be collected on another level from this study. The bed request times, bed assignment times, and move times for elective, urgent, and transfer patients would need to be gathered for analysis.

This study has the potential to be developed into a model used as a decision support system. Besides quantifying effects on ED crowding, the decision support system could be used to assess the benefits versus the costs of various operational and strategic alternatives.

Conclusion

This study proposed a hospital patient flow simulation model to gain insights into the relationship between home hospital programs and ED crowding. The model in this study quantifies the effects of a home hospital program on ED boarding and inpatient bed demand. In particular, the model captures ED boarding rates for various home hospital cases, home hospital admission statistics, and freed bed hours. Often in home hospital literature, these concepts are discussed conceptually. However, this is the first time to our knowledge that home hospital's effects on freed beds and on ED boarding have been calculated so systematically and comprehensively.

While some of the home hospital impacts on ED boarding were significant in this study, the decreases may not be practically significant. More specifically for our hospital setting of a large, urban, high acuity, teaching hospital, home hospital makes no significant impacts to boarding. The quantitative effects presented in this study help to build a foundation for hospital leaders to understand what kind of impacts home hospital makes to ED boarding and inpatient bed demand. This knowledge can help a decision maker assess whether to implement a home hospital program or not.

Further, this study provides insight into the varying factors of different home hospital programs, which hospital leaders can use to determine what kind of home hospital program they would like to implement. The analytical insights for the different types of programs allow decision makers to weigh pros and cons of each and to target their goals. The stringent limitations of ED referral programs, with respect to length of stay and ICU bed requests, versus the flexibility of the inpatient-transfer referral

programs are identified and exemplified in our results. We find hours of operation to be a significant restriction on ED referral programs as well.

The presented modeling methodology for analyzing home hospital and ED crowding can also be used as a modelling format for researchers and practitioners for analytical purposes in future studies. The clinical eligibility rates are established for various patient mixes. The home hospital characteristics, rules of operation, and principles presented can be utilized for future use and improvement.

APPENDIX A

MODEL VALIDATION

Table 20 Priority Bed Clean Scenarios

Day	Timeframe	# Beds Available in Unit	Bed Requests	Bed Exits	Bed Unit Type
4	3pm-5pm	0	2	3	Medical
5	11am-1pm	0	3	4	CCU/Telemetry
10	3pm-7pm	0	5	5	Surgical
11	4pm-8pm	0	6	8	Medical
17	4pm-8pm	0	5	5	Medical
18	3pm-4pm	2	4	2	Telemetry
18	10pm-12pm	0	(2) ¹	2	ICU
19	3pm-6pm	0	3	3	Neuroscience/Medical

Note 1: (·) designates bed requests that occurred prior to timeframe in which bed clean priority occurs.

Table 21 ED boarding delay assumption

Day	Hour of Bed Request	Boarded Time (hrs)
9	2 pm	14
15	9 am	8
15	10 am	10
15	11 pm	23
15	11 pm	22
23	12 pm	14
25	10 am	9.5

Table 22 Anderson-Darling Normality Test Results

Day	p-value
1	0.431
2	0.179
3	0.260
4	0.294
5	0.916
6	0.676
7	0.627
8	0.988
9	0.069
10	0.068
11	0.080
12	0.510
13	0.558
14	0.830
15	0.766
16	0.349
17	0.236
18	0.356
19	0.803
20	0.702

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